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EPSCoR Supplemental Grant for An Application of Neural Networks to Seismic Signal Discrimination

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Tech Foundation, Inc.
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Montgomery, West Virginia 25316

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The EPSCoR Supplemental Grant for An Application of Neural Networks to Seismic Signal Discrimination was used to fund a Graduate Student for work with a parent ARPA project. The students course and research activities are presented along with a copy of the completed Masters Thesis based on the application of an ARMA model for seismic event discrimination.

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1. Overview

Funding for an EPSCoR student in the area of control systems engineering (masters level) was requested and received as a supplement to an ARPA funded project "Application of Neural Networks to Seismic Signal Discrimination". This EPSCoR funded student was directly involved in the application of neural networks and fuzzy logic as part of the investigation of seismic signal detection and classification. The graduate advisory committee for the EPSCoR student was comprised of three faculty members directly involved in the research project.

Two different students filled the EPSCoR funded position. Initially, Mr. Mike Murphy was selected based on undergraduate achievement and supplemental sponsorship by Eagle Research Corporation of Charleston, West Virginia. Eagle Research provided Mr. Murphy with a two year leave of absence from his employment and agreed to continue insurance benefits and provide material support in Mr. Murphy's endeavors. Mr. Murphy completed one semester on campus but chose to return to full time employment upon learning of his wife's pregnancy towards the end of his first semester. Mr. Murphy left under favorable circumstances and continues his studies as a part time student. A second student, Mr John Martin, began his program of study the same time as Mr Murphy as a research assistant on the ARPA funded project and assumed the role of EPSCoR student the second semester of the program

The goals of the EPSCoR position was for the active participation of the student in the parent research project working with the principle investigator and co-investigators in developing mathematical models of neural networks and implementing both neural nets and fuzzy logic. The student was expected to prepare and present a major paper. Mr Murphy prepared a paper entitled "Neural Network Techniques Applied to Seismic Event Classification" that was presented at the South East Symposium on System Theory, University of Alabama, March 8, 1993. Mr Martin has prepared and has been notified of acceptance of a paper at the West Virginia University Mining Symposium to be held July 11, 1994

Mr Martin's role in the parent project was substantial. He was instrumental in writing the major parametric transformation codes used in the extensive network testing schemes. His main research involved the application of neural networks to seismic discrimination using an ARMA signal model. This work was used as his required masters project and the final version, as presented and approved by WVIT graduate school, is attached to this report

main research team covering topics such as programming in ADA, various neural networks, and presentations on seismology.

3 Research Related Activities

Course attendance and work assignments were expected and assumed in connection with the students program of study. Other project related activities outside the normal realm of course study enhanced the EPSCoR students learning experience.

An Intel Neural Network Development System was purchased for use by the student as part of his research program. Use of this system allowed the student to independently study neural networks from a users point of view as well as conduct research on training and classification of different seismic parametric data transformations. The students was required to prepare and present a seminar on Intel System to the research group. Additionally, he trained other members of the research group in the use of the development system for preliminary testing of the main seismic data sets. The conference paper written by Mr. Murphy was based on test results obtained form the development system. Mr. Martin extensively used the development system in his preliminary ARMA modeling work. The development system was used mainly for quick experimentation and education. The software was not used for final result tabulation due to speed limitations and copy restrictions.

A mathematics software package, Matlab, was used by the research project to pre-process the raw seismic waveforms and derive different parametric transformations. The EPSCoR student was responsible for taking the rough transformations developed by the co-investigators and modify the routines into the proper format used for test result generation. These modifications ranged from re-coding the algorithms for more efficient operation to the addition of data file manipulation routines that allowed auto execution of data processing routines.

The process of selecting a masters research project lead to the exploration of combinations of the different parametric transformations for presentation to the neural networks for training and testing. A detailed study of the size and amount of overlap needed in the windowing of the seismic waveforms is presented in the masters project paper attached to this report.

4 Travel

Part of the EPSCoR students funding was utilized for travel. The following travel was conducted by the EPSCoR student.

1. South East Symposium on System Theory, University of Alabama, March 8-9, 1993, Alabama. The EPSCoR student attended multiple sessions at the conference and a student paper was presented.

2. Artificial Neural Networks in Engineering, St. Louis, Missouri, November 11, 1993., The EPSCoR student attended an eight hour tutorial session on neural networks as well as attending three days of paper presentations.

3. Research trip to the Center for Seismic Studies, Arlington, VA. This trip introduced the EPSCoR student to some of the members of the Centers staff as well as providing an opportunity to ask several questions to the Centers staff pertaining to the seismic database.

4. West Virginia University Symposium on Mining, July 11, 1994. The EPSCoR student will present a paper on research findings at this conference.

5 Summary

The EPSCoR funded position provided a rich environment for the student involved above and beyond that of the normal graduate student at West Virginia Tech. The direct interaction with research faculty, provision of office space, computer equipment, neural network development tools, and travel money allowed the student to fully develop the skills and knowledge needed to conduct research. The additional resources of the parent research project made available an extensive research database and additional computer facilities at the Center for Seismic Studies. While the research project was not a thesis in the traditional sense, many of the elements of the project paper re-enforced the skills necessary to conduct applied research and report the results.

Seismic Event Classification using Neural Networks with ARMA Coefficient Modeling

A Masters Project

Presented to
The Faculty of the Graduate Program
West Virginia Institute of Technology

by

John R. Martin

In Partial Fulfillment
of the Requirements for the Degree
MASTER OF SCIENCE
Control Systems Engineering

April 26, 1994

AN ABSTRACT OF A MASTERS PROJECT

SEISMIC EVENT CLASSIFICATION USING NEURAL NETWORKS WITH ARMA COEFFICIENT MODELING

John R. Martin

Master of Science in Control Systems Engineering

An artificial neural network is incorporated as part of a software simulation system for the purpose of classifying seismic events from waveform data. Neural network techniques augment traditional methods of seismic event classification to enhance classification flexibility and accuracy. Unprocessed seismograms are not well suited for presentation to neural networks because of the large number of data points required to represent a seismic event in the time domain. Parametric representation of the seismic waveform numerically extracts those features of the waveform that enable accurate event classification.

Coefficients of an Auto-Regressive Moving Average (ARMA) model are extracted to form a parametric representation of a seismic event. This parametric representation provides adequate information for accurate event classification, while significantly reducing the minimum size of the neural network. The data set is comprised of 75 wave forms, five signal classes, with 2400 samples per seismic trace. Each waveform in this database is parametrically represented by the windowed ARMA feature extraction stated above. These features are presented to the neural network for classification.

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1.0 INTRODUCTION

In recent years, detection and classification of seismic events have been studied extensively and require nighly trained seismologists to accurately interpret seismic traces.

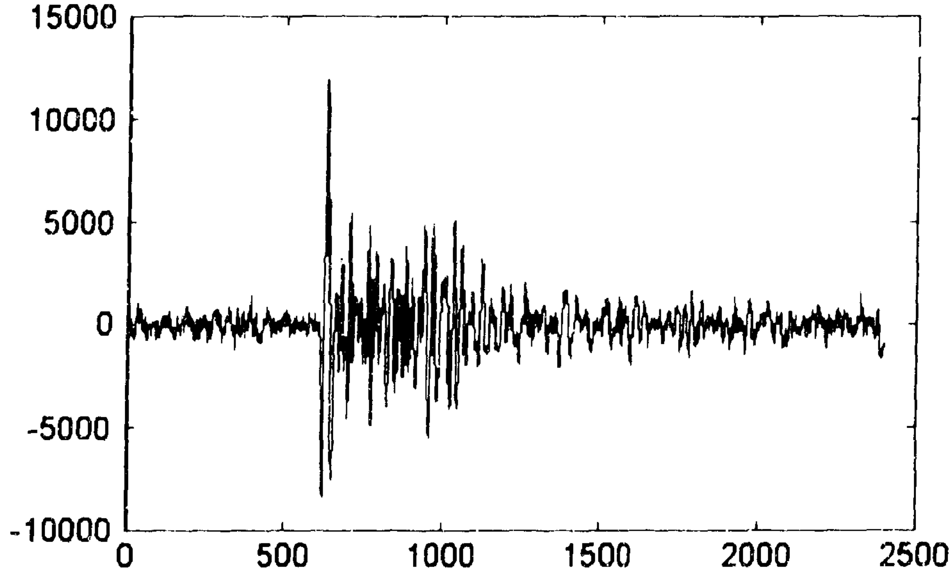

Figure 1 Time Series Plot of FEBME16.W

Figure 1 presents the seismic trace of a typical marine explosion. There are two methods which a seismologist might use to classify a seismic event. The easiest event classification occurs when information such as location and time are known prior to the event occurrence. Seismologists are then prepared to monitor the event and may easily verify the event type and location. The second method does not provide the seismologist with information prior to the event occurrence. Without this a-priori knowledge, the seismologists job becomes significantly difficult.

Upon initial examination of a seismic trace, a seismologist would begin the classification procedure by identifying features of the seismic event. Typical features of interest are the arrival and amplitude of primary surface waves, secondary waves, and long waves. After the initial phase identification, a classification is tentatively associated with the waveform. The seismologist would attempt to confirm the trace origin and type with someone at the event location or through published schedules of such events. To improve the probability of a correct classification, this procedure is usually verified by other seismologists.

Signal classification of this type is time consuming and is prone to error in interpreting the signal phases and arrival times. To a great extent, this type of signal classification is subjective at best. The purpose of this project is to determine the usefulness of a neural network in seismic event discrimination.

1.1 Project Description

Seismologists use heuristics and intuition in classifying seismic traces. The heuristics are based upon various features of the signal. Extraction of these various features, as performed by the seismologist, can introduce significant error in signal discrimination.

Feature extraction and classification error can be reduced by implementing these functions in an expert system. Heuristics, or rules of thumb, suggest parametric transformations that could potentially prove useful in developing a neural network based system. Since each signal in the seismic trace database consists of 2400 points, an excessive amount of data for a neural network, some method of data reduction must be

included One such method of parametric data reduction is in calculating the Auto-Regressive Moving Average (ARMA) filter coefficients This method will be used to determine if the frequency content of the event and how it changes over the event life provide any useful information in discrimination of seismic events Classification of seismic signals will be evaluated using supervised Kohonen and Back-propagation neural networks.

1.2 Scope of Activities

Determination of neural network usefulness in classifying seismic traces will require collecting known data for training and testing, development of ARMA coefficient calculation, research on back-propagation and Kohonen neural networks, and performance evaluation of the algorithms. Specifically, the project scope involves:

- Data collection
- ARMA coefficient development
- Signal preprocessing
- Back-propagation research and development
- Supervised Kohonen research and development
- Neural network training and classification
- Examination of results.

1.3 Report Overview

A brief description of the problems in seismic event classification has been provided along with an approximate research plan The remainder of the paper discusses those topics in detail

Chapter 2 describes the data base used for testing as discussed throughout this paper. The various tables listed in Appendix A with seismic wave form names, stations and Julian dates are sufficient references such that anyone accessing the on-line data base at the Center for Seismic Studies can retrieve the related seismic wave forms. Appendix B provides seismic monitoring station information.

Chapter 3 offers background information on seismology. The broad classification of seismic events as used by seismologists is presented along with plots of sample wave forms. Qualitative assertions and heuristics that are commonly used for seismic event classification are discussed.

Seismic parametric conversions are covered in Chapter 4. Parametric data is derived from the sampled wave form and is independent of the identification of various seismic phases associated with most classification schemes. The parametric data is derived from ARMA coefficients. Appendix C contains the Matlab script file for the ARMA coefficient extraction.

Chapter 5 describes the neural networks utilized in the training and testing of the seismic parametric data. Basic neuron models, activation functions, neural network structure, network training methods, and differences between back-propagation and Kohonen neural networks are discussed at the introductory level

Test results, network training times and performance, and remarks are covered in Chapter 6. Detailed test results are included in Appendix D.

2.0 SEISMIC DATABASE

The Center for Seismic Studies (CSS) is an agency funded by the Advanced Research Projects Agency (ARPA) with the principle objective of providing the research community easy access to seismic data. Since 1982, CSS has been improving the teleseismic database procedures and programs of the Lawrence Berkeley Laboratory and the Discrimination Group at Lincoln Laboratories. A more progressive database was needed to meet the standards of the seismic research community and an interactive method needed to access the database. In 1987, the version 2.8 database was released adhering to the Intelligent Array System (IAS), a type of seismic data collection standard. The version 2.8 database also embedded Ansi Standard Query Language (SQL) to interactively access the seismic database. In 1989, CSS modified the version 2.8 database to handle regional as well as teleseismic events. The modified database, Version 3.0, also has a simple database structure that was less complicated for the interactive use and lessened maintenance.

2.1 Databases at the Center for Seismic Studies

The Seismic Operations LAN (SOL) is the primary host for interactive analysis from the seismic research community. SOL is automated to collect and process external seismic information from various international seismic stations. Using the processing power of a SUN workstation, SOL is the heart of the interactions of CSS to the seismic community. The Central Data Repository (CDR), the seismic data archives of CSS, is the storage facility for SOL. The CDR consists of a 600 Gigabyte Tape drive system dedicated to waveform storage, a 6 Gigabyte database management system, and a 400

Gigabyte Optical Jukebox to store satellite imagery, map graphics, and waveform segments. Figure 2 displays the current configuration at CSS.

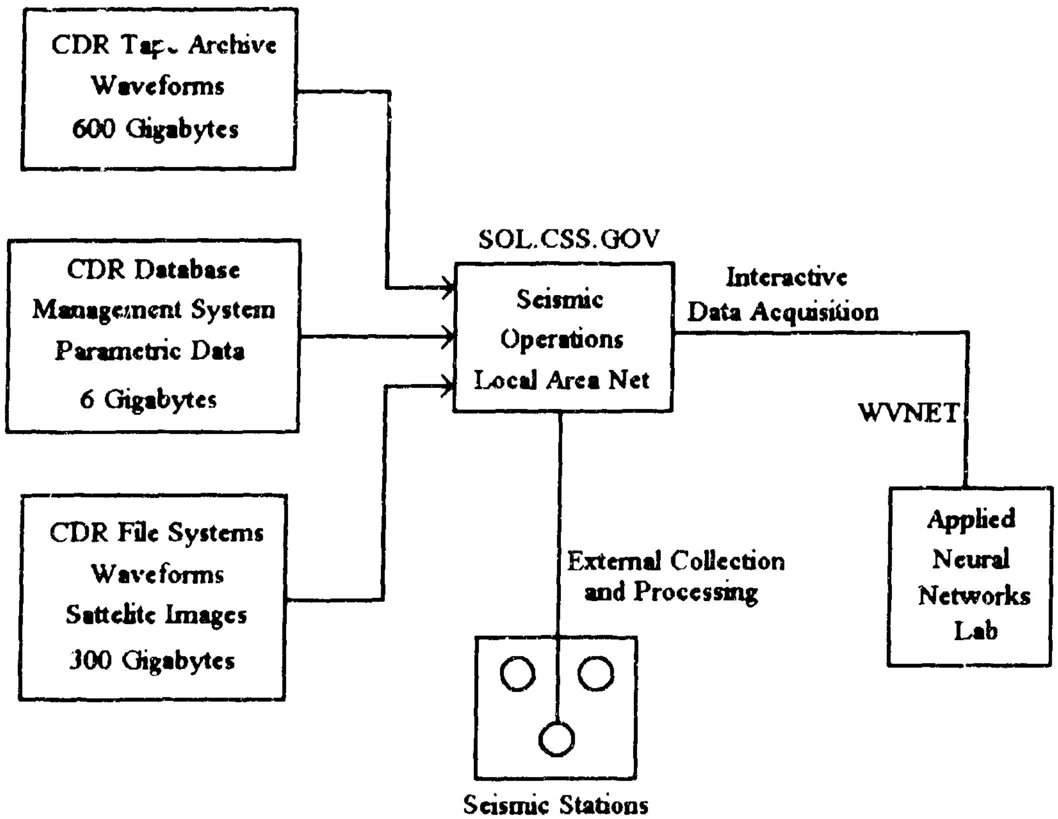

Figure 2 CSS Database

Although the Center has many databases consisting of seismic data that has been collected worldwide, the three major databases are the GSETT, the IMS, and the EXPLOSION. These three databases represent 75% of the entire parametric and waveform data stored at the Center.

The GSETT database was the work of the *Ad Hoc Group of Scientific Experts to Consider International Co-Operative Measures to Detect and Identify Seismic Events,*

called GSE [6]. GSE was formed in 1976 by an international group of scientists during the Conference on Disarmament for the sole purpose of exchanging data useful for monitoring a limited or comprehensive nuclear test-ban treaty. Using approximately 50 international seismic stations, GSE conducted the first international exchange of seismic data in 1986 during the GSETT-1 test. Due to the complexity and size of the exchange of parametric and waveform data, the test was only a limited success [6]. Waveform data were to be available on request, but never exchanged routinely. But with the increasing technology and the availability of larger computer networks, the second international full-scale test was conducted from the 22nd of April 1991 to the 2nd of June 1991. During these 42 days, over 3,700 seismic events were classified and 85,000 waveform segments were collected and stored into 1.2 Gigabytes of information. Although, the second international test had some small procedural problems, the test was a seismological success [6].

The Intelligent Monitoring System (IMS) is a ARPA-sponsored computer system for automated processing and interpretation of seismic data recorded by arrays and single stations. It was integrated into CSS computer systems, and has been operational since 1990. The IMS data has been cataloged in the IMS database at CSS, which contains seismic traces from the two largest seismic stations in Norway, ARCESS and NORESS ARRAYS.

The EXPLOSION database consists of all unclassified seismic data on nuclear testing. Another database currently being investigated is the GROUND TRUTH database, created by Lori Grant at CSS [12]. This database is currently being compiled from both the IMS and GSETT databases. The GROUND TRUTH database consists of a hand picked group of seismic events that were verified through means of seismic bulletins, mining records, and personal contact. Although the database has been released to the

public, the number and type of events are not sufficient for training and testing a neural network as investigated in this research. The database presently consists of 62 waveforms with sample rates and durations that vary. A fixed sample rate and duration was needed for the development of ARMA models.

2.2 Applications at the Center for Seismic Studies

The heart of database management at CSS is the SQL/ORACLE database host. This gives users an interactive method of accessing data. Since SQL querying can be quite taxing, CSS has created some tools making the collection and examination of data easier. To make the seismic tools accessible from many different operational platforms, CSS programmed the tools to be used as Xwindows applications.

CENTERVIEW was the first programmed tool from CSS [2]. Using this tool, one can directly access the database without using the burdensome SQL queries, and still have the power to select the data on a variety of constraints. With this program, one can compile data for downloading, review parametric data, and transfer data to the other seismic tools. The next tool was *MAP*. This tool displayed the location of the seismic events [epicenters] and the location of the seismic stations that recorded each event. These locations can be displayed on a variety of geographic maps stored at CSS by using the *MAP* program. The last tool created was *GEOTOOL*. This tool gives researchers the ability to view the waveform in a time series plot, seismogram. It also has some signal processing capabilities such as FFT's, filtering, spectrogram, and others.

2.3 Research Database

The research database, *SUBSET1*, is a subset of the GSETT and IMS databases. *SUBSET1* contains 75 seismic traces composed of 5 event types with 15 waveforms each. The event types selected included both man-made and natural events as follows;

- marine explosions
- quarry blasts
- local
- regional and
- teleseismic.

The waveforms were recorded in the Euro-Asian area with a fixed wavelength of 2400 samples and a sample rate of 20 Hertz. Each event classification was verified through the *REMARKS* database table [1].

3.0 SEISMIC BACKGROUND

The various aspects of seismology include observational seismology, instrumental seismology, theoretical seismology, and data analysis of seismic events. The primary focus of applying neural networks to seismology was the analysis and subsequent classification of seismic data. Some introductory terminology as applied to seismic data analysis will be reviewed.

3.1 Seismic Event Classifications

The types of seismic events can be roughly divided into two categories: natural and man made. Natural seismic events include tectonic plate movement, volcanic activity, collapse earthquakes, and oceanic microseisms. Man made seismic events can be the result of a controlled event or that of an induced event. Controlled events are typically explosions and cultural noises while induced events will result from reservoir impounding, mining, quarry and fluid injection. Table 1 lists the broad categories of natural and man made seismic events.

Seismogram interpretation is dependent on the location of the recording station and the type of structural model utilized for wave propagation in the geological region of the recording station. The structural models and propagation paths have lead seismologists to three different categories of seismic events, without regard to the source of seismic activity. These categories are based on distance between the source epicenter and the recording station. It is common practice to use a spherical model of the earth and express the distance from seismic event focus to the recording station as the angle

subtended at the center of the earth between the focus and the station ($1^{o} = 111$ km). The categories thus established are:

Local events	$< 10^{o}$
Regional events	10^{o} to 20^{o}
Teleseimic	$> 20^{o}$

Table 1 Types of Seismic Events

Natural events:
- tectonic
- volcanic
- collapse earthquakes
- ocean microseisms

Man Made - Controlled
- explosions
- cultural noises

Man Made - Induced
- reservoir impounding
- mining
- quarry
- fluid injection

Raw seismograms are relatively lengthy. Typical sampling rates vary between 20 Hz to 40 Hz with high frequency instruments operating at sampling rates up to 1 KHz. The duration of seismic events range from a few minutes for discrete events to day for seismic swarms. Seismograms used in this research all result from discrete events sampled at 20 Hz, with a total of 2400 data points per sampled waveform. Waveforms were taken from the GSETT database at the Center for Seismic Studies. Figure 1, shown below, illustrates a typical marine explosion. The start of the seismic event occurs at

sample number 600. This starting alignment represents a 30 second pre-event leader and is common for all seismic traces used in the GSETT database.

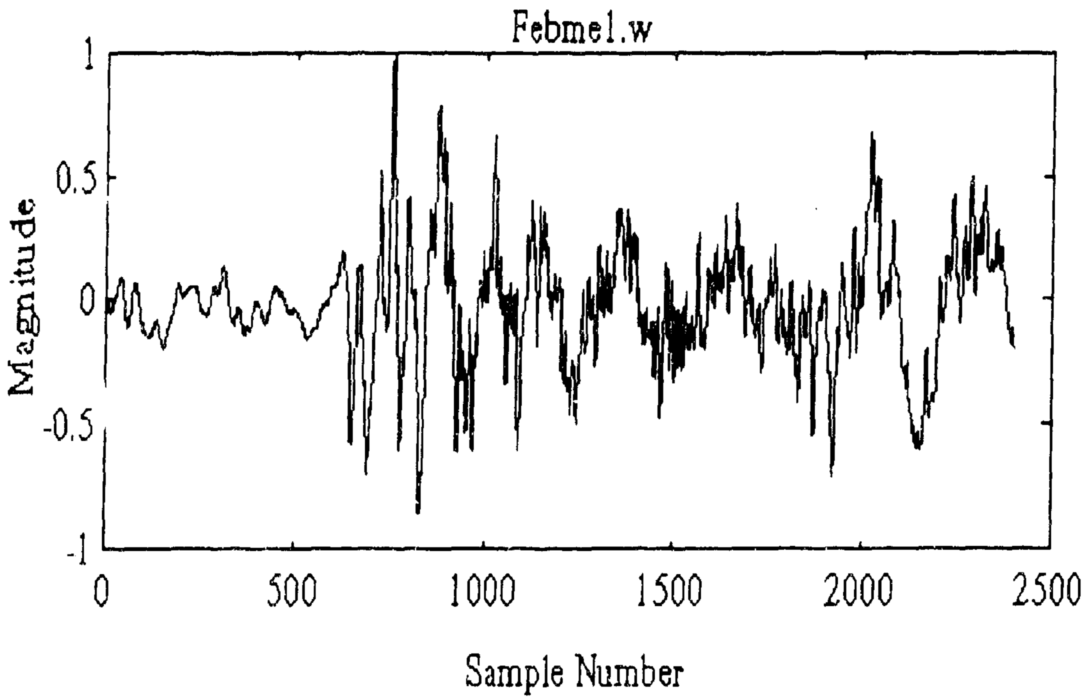

Figure 3 Marine Explosion Febme1.w from GSETT Database

In analyzing waveforms such as the one presented in Figure 3, seismologists will identify different phases of the seismogram based on the time of arrival and the mode of propagation through the earth.

There are two basic types of seismic waves, body waves and surface waves [21]. Body waves are radiated by the seismic source and propagate in all directions while surface waves are concentrated along the surface. Body waves can be further subdivided into compressional (longitudinal) and shear (transversal) waves. Compressional waves are

often called primary waves or P waves and transversal waves are called secondary or S waves. P waves tend to travel at a rate 1.7 times that of S waves and are normally the first portion of the seismic waves to be present in a seismogram.

The P waves are always the first waves to arrive [21, 34]. The P waves are surface waves that cause the rock particles to oscillate back and forth in the direction of propagation and can be compared to the propagation of sound waves. S waves cause rock motion perpendicular to the motion of P waves and represent a shear wave. Motion of S waves through the liquid parts of the earth's interior is not possible since liquids do not sustain shear forces. Two additional waves often associated with a seismic event are the LQ and LR surface waves. The L stands for long , Q represents Love waves and R is Rayleigh waves [21]. These two waves are often dominate in terms of relative amplitude. Love and Rayleigh waves exhibit velocity dispersion which can be observed as frequency variant whereas P and S waves tend to be velocity invariant.

The P, S, LQ, and LR, portion of the seismic trace are referred to as phases. These phases are further subdivided to give indication of propagation path. A Pn or Sn phase indicates a path that is in the upper crust and is confined to the granitic layer. Reflection of phases are possible off other layers in the earth. A phase reflected off the Moho layer is referred to as a PmP or SmP phase [21]. Many other combinations are used as dictated by the seismic event being evaluated.

3.2 Analysis of a Regional Seismic Event

A regional seismic event from the GSETT data base is now presented to illustrate the type of parametric information determined by a seismic analyst. Data base notation as

assigned by the Center for Seismic Studies is utilized in the seismic event description that follows. The regional event considered is illustrated in Figure 4 The event is assigned an origin identification within the GSETT data base of ORID = 36907. This event occurred on April 28th, 1991 [Julian date of JDATE = 1991117], and was determined to be a regional event. A summary of the seismogram analysis is given in Table 2.

The STASSID label represents a station association identification number assigned as part of the data base record. The wave train of a single event may be made up of a number of arrivals and the STASSID allows arrivals believed to have come from a common event to be joined together in the data base.

The signal amplitude is denoted AMP and represents a zero to peak amplitude of the earth's displacement in units of nanometers. The duration of a particular phase is designated PER and is in units of seconds.

Figure 4 is a regional event with three recorded phases. The magnitude scale was normalized to +/- 1 with actual displacement magnitudes indicated in Table 2. The first arrival wave is the Pn wave that traveled through the earth's crust from the epicenter to the recording station A secondary surface wave, Pg, arrived from a deeper propagation path followed by a large magnitude LQ or Long-Love wave. The first 618 sample points (approximately 30 seconds) before the arrival of the Pn wave is a period of no seismic activity. This represents normal background noise and will tend to drift in magnitude throughout the course of the day due to cultural noises.

The recording station for this particular waveform was located in Boyern, Germany It was recorded with a single vertical channel that measures earth displacement. Table 3 gives the station location and instrument calibration factors The frequency

response of the instrument is plotted in Figure 5. The 3 dB bandwidth is 3 Hz. A usable bandwidth of about 10 Hz can be created with appropriate inverse filtering of the seismic waveform.

TABLE 2 Seismic Analysis of Regional Event FEBR9.W

ORID	36907
Date	April 28, 1991
Julian Date	1991117
Event Time	672777893.300 seconds from January 1, 1970.
Classification	Regional event
Recording Station	Grafenberg Array, Boyern, Germany (GRA1)

Event Location

Latitude	46.22°
Longitude	15.44°
Depth	8 Kilometers

Phase Information

3 phases recorded at GRA1
Surface Wave Magnitude measured at 2 nanometers
Body wave Magnitude measured at 3.50 nanometers

Phase Summary

Phase	Start Time	Start Sample number	ARID	STASSID	AMP	PER
Pn	672777957.3	619	492530	368441	41.2	0.65
Pg	672777971.3	886	492531	368442	323.6	0.082
Lg	672778033.8	2136	492532	368443	468.0	0.71

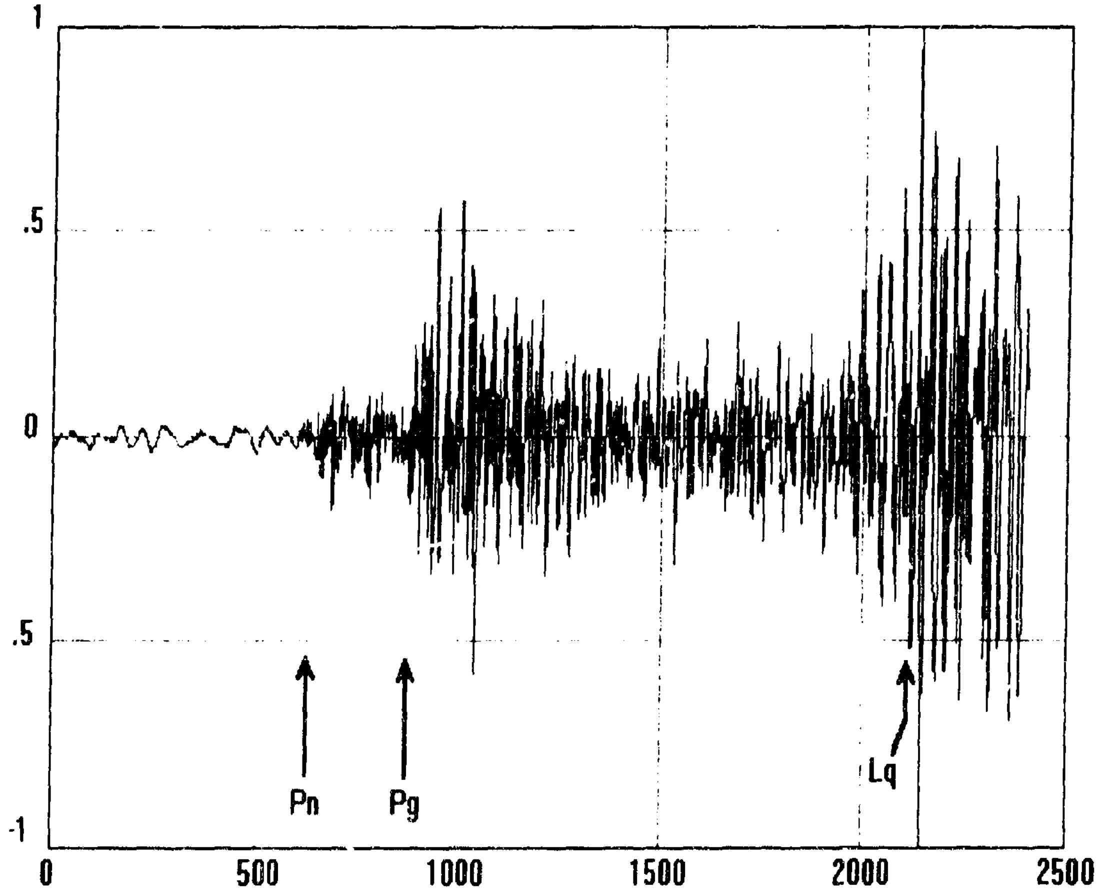

Figure 4 Regional Seismogram of FEBR9.W

Table 3 Station Information

GRA1 - Grafenberg Array -- Boyern, Germany

Single Station	
Channel Type:	bz
Channel Id:	51671

Location

Latitude	49.692°
Longitude	11.222°
Depth	0.5 Kilometers From Mean Sea Level

Noise Measurements - Correction Factor

Mean Noise -	6.5 nM
Stand Dev	-0.2 nM
Signal to Noise Threshold	1.5

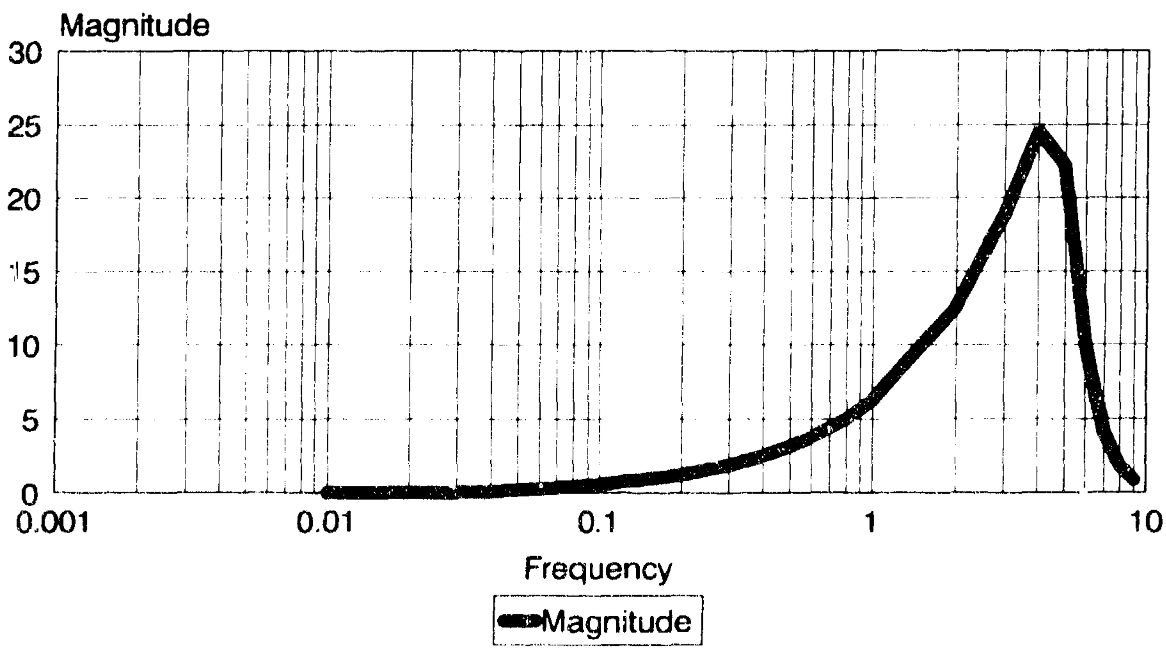

Figure 5 Frequency Response of Grafenberg Array Channel bz

3.3 Qualitative Assertions and Heuristics

When evaluating a given seismic event, the seismologist must base his reasoning on a physical model of the earth with respect to the recording station location and the suspected seismic epicenter. Qualitative assertions, based largely on the identification of seismic phases, must be made concerning the propagation in a global scale. Table 4 lists several such qualitative assertions.

Table 4 Qualitative Assertions

1. The dominant frequency of the seismic signal is inversely proportional to the distance of the event.

2. The Pg wave is the first arriving wave for local events, Pn for regional events P or PKP for teleseismic events.

3. The longer the duration, the greater the magnitude.

4. Presence of a strong S-wave is a distinctive feature of natural events such as earthquakes.

5. The absence of S-waves or weakness with respect to P waves indicate an explosive or artificial seismic source.

6. Similar waveforms are present in seismograms that originate in the same seismological area.

These assertions may be supplemented by seismologist developed heuristics as listed in Table 5. Many of the heuristics can be utilized as linguistic descriptors in the development of a neural network seismic event discriminator.

Table 5 Seismic Heuristics

1. If the duration of a signal is less than one second, it is most likely noise.

2. If two different signals have dominant signals whose ratio is above 10, then they probably belong to two different events.

3. If the dominant frequency of the first arrival is above 7 Hz, then the seismogram belongs to a local event.

4. If the dominant frequency of the first arrival is between 2-7 Hz , then it belongs to a regional event.

5. If the dominant frequency of the first arrival is below 2 Hz then it belongs to a teleseismic event.

6. The beginning of a seismic event can be detected using Dixon's test [10].

7. Cultural noise will have dominant frequencies above 1 Hz.

8. Microseismic events will exhibit low frequency broad band noise from less than 0.01 to 0.5 Hz with periods of 2 to 100 seconds.

9. P wave is normally recorded first.

10. P is normally followed by S, LQ, and LR.

11. P waves have linear polarization.

12. LR will have elliptical polarization.

13. Earthquakes produce approximately equal amounts of P and S waves.

14. Explosions produce more P waves than natural events.

15. Earthquakes give anaseismic and kataseismic first onsets.

16. Explosions give anaseismic first onsets everywhere.

17. Earthquakes have relatively deep foci.

18. Explosions have shallow foci.

19. Wave train durations are shorter for explosions than for earthquakes

Most of the qualitative assertions and heuristics are based on the various phases of a waveform as identified by a seismologist. The listed assertions and heuristics offer several clues which aid in the development of neural network parametric conversions.

The heuristics dealing with dominate frequency raised questions as to the usefulness of the remaining frequency information. One method of obtaining additional frequency information is through generation of the ARMA filter coefficients which will be discussed in Chapter 4.

4.0 ARMA COEFFICIENT MODELING

Several of the heuristics stated in Chapter 3 deal with the dominant frequency of the first arrival wave of a seismic signal. These heuristics offer information on local, regional, and teleseismic events only; no information is provided for man-made events such as marine explosions or quarry blasts.

Since the given heuristics are limited to natural events, additional information must be provided for further discrimination of man-made events. One method of creating this information is in generating the power spectrum for each seismic event. The power spectrum may be obtained by processing the time series data through a FFT. However, the resulting frequency data is as large as the original time data. As the original time series contains 2400 points, the data size must be reduced since a 2400 point vector is excessively large for neural network training and classification.

The power spectrum information may be retained while significantly reducing the volume of data through calculation and use of the ARMA filter coefficients. The ARMA filter is designed from the time series data and can approximate the original frequency response with a filter of proper order.

As the ARMA model significantly reduces the amount of data, it was decided to include information pertaining to the frequency variation over time which is accomplished by windowing the time series data. The process of windowing divides the data into a specified number of consecutive segments. Each segment or time slice is usually of equal size or duration.

4.1 ARMA Model Derivation

The time domain design problem can be stated as follows:

Given a sequence g(n), n = 0, 1, ..., K, design a digital system of prescribed degree such that its impulse response h(n) approximates g(n) as well as possible.

This problem arises as an unusual design task. In many cases, g(n) is the sampled output of a continuous system. When this occurs, the unknown system is to be modeled by a rational transfer function. The modeling of the system is very important. The modeling procedure described here was named for Prony who developed it in 1795 for problems in gas and hydro mechanics [23].

Let the transfer function H(z) be designed to be

$$H(z) = \frac{\sum_{k=0}^{p} b_k \cdot z^{-k}}{1 + \sum_{k=1}^{p} a_k \cdot z^{-k}} = \sum_{n=0}^{\infty} h(n) \cdot z^{-n} \tag{4.1}$$

where p is an element of the set of natural numbers. Here, the order of the numerator and denominator are assumed to be equal. First, the number of given values g(n) is chosen to be equal to the number of coefficients to be determined. At least one recursive system always exists, the impulse response of which satisfies exactly the condition

$$h(n) = g(n), \quad n = 0, 1, \ldots, K . \tag{4.2}$$

Multiplying Eq. (4.1) by the denominator, substituting for Eq. (4.2), and comparing the terms of equal order, you get the matrix equations shown below.

$$\left[\begin{array}{c} b_0 \\ b_1 \\ \vdots \\ b_{(p-1)} \\ b_p \\ \hline 0 \\ \vdots \\ 0 \end{array}\right] = \left[\begin{array}{ccccc} g(0) & 0 & \cdots & & 0 \\ g(1) & g(0) & & & \vdots \\ \vdots & & \ddots & & \\ g(p-1) & & g(1) & g(0) & 0 \\ g(p) & \cdots & g(2) & g(1) & g(0) \\ \hline g(p+1) & & & g(2) & g(1) \\ \vdots & & \ddots & & \vdots \\ g(2p) & & \cdots & g(p+1) & g(p) \end{array}\right] * \left[\begin{array}{c} 1 \\ a_1 \\ \vdots \\ a_{(p-1)} \\ a_p \end{array}\right] \qquad (4.3)$$

The indicated partition in Eq. (4.3) leads to the pair of matrix equations

$$\mathbf{b} = \mathbf{G}_1\mathbf{a} \qquad (4.4a)$$

$$\mathbf{0} = \mathbf{G}_2\mathbf{a} \qquad (4.4b)$$

where $\mathbf{G}_1$ is a (p+1) x (p+1) lower triangular toeplitz matrix, and

$$\mathbf{G}_2 = [\, \mathbf{g}_1, \mathbf{g}_2, \ldots, \mathbf{g}_{p+1} \,] \qquad (4.4c)$$

is a p x (p+1) rectangular matrix. Equation (4.4a) yields the vector $\mathbf{b}$ of the numerator coefficients for any denominator such that the impulse response has the desired values for $n = 0, 1, \ldots, p$.

To calculate the denominator, we write Eq. (4.4b) as

$$\mathbf{0} = \mathbf{g}_1 + [\, \mathbf{g}_2, \ldots, \mathbf{g}_{p+1} \,] * \mathbf{a}'$$
$$= \mathbf{g}_1 + \mathbf{G}_3 * \mathbf{a}'$$

where $\mathbf{a}' = [\, a_1, a_2, \ldots, a_p \,]^T$ is the vector of the unknown coefficients.

If G3 has rank p, we obtain

$$\mathbf{a}' = -\mathbf{G}_3^{-1} * \mathbf{g}_1 \,. \tag{4.5}$$

Together with **b** from Eq. (4.4a) we then have the coefficients of H(z).

4.2 ARMA Coefficient Extraction

Once the method for creating the ARMA coefficients has been determined, the next step is to implement the feature extraction. The Prony method as described above handles ARMA modeling through matrix manipulation. At this point, the Matlab™ software package was chosen for feature extraction. Matlab is a software package which was written for the processing of mathematical functions especially in its handling of matrices. The Matlab script file used to extract the ARMA coefficients is included in Appendix C. Direct implementation of the Prony method can be accomplished using the *prony* command [25]. The command format is

[b , a] = prony(h, nb, na)

where b = numerator coefficients in descending powers of z

a = denominator coefficients in descending powers of z

h = desired impulse response

nb = numerator order

na = denominator order.

After calculating the filter coefficients, the results are stored with the exception of the constant 1 of the denominator. This constant 1, the a_0 term, was left out of the training data since it would be the same for each signal and provided no significant information to the neural networks for training or classification.

The next step in creating a reduced parametric data set is in determining the number of windows and the filter order required to optimize neural network training and classification. By varying both the number of windows and filter order between 8 and 24, a series of 25 data sets were obtained. Each data set was divided into a 45/30 split, 45 signals for training and 30 signals for classification, then placed into a back-propagation neural network for training and classification. Network training was limited to 1000 epochs before event classification.

Table 6 contains the window size and filter order testing. The data of highest importance is the classification percentage From Table 6, it can be determined that using 16 windows and a fourth order ARMA model will provide the best training and discrimination results This modeling will reduce the size of each signal from 2400 poitns to 144 points

Table 6 Test Data for Determining Window Size and Filter Order

Number of Windows	Filter Order: 2	3	4	5	6
8	57 / 10	80 / 6.7	80 / 10	80 / 15	83 / 16
12	78 / 20	87 / 23	84 / 30	86 / 26	86 / 23
16	96 / 13	93 / 22	93 / 35	94 / 30	90 / 26
20	90 / 12	94 / 18	92 / 20	93 / 22	93 / 22
24	94 / 10	95 / 12	95 / 13	94 / 15	95 / 10

Note: Table format is a / b where a is the training % and b is the classification %

A comparison of the frequency plots of the time series and ARMA model demonstrates the information contained in the reduced parametric data. Figure 6 gives the time series frequency plots for Febme16.W over the chosen four windows. The resulting ARMA filter frequency response plots are contained in Figure 7. A comparison of the respective windows shows the ARMA model to contain the same frequency information as the time series. The resulting ARMA plots are significantly smoother than the time series plots. This is due to the time series plots being created from the actual frequency information contained in the signal while the ARMA plots show the true frequency response curve. The plots shown in Figure 6 and Figure 7 are normalized to a magnitude of one (1) to eliminate any amplitude information. Elimination of amplitude information can be justified as the original project intention was to determine the usefulness of frequency information other than the frequency heuristic of the first arrival wave which was described in Chapter 3.

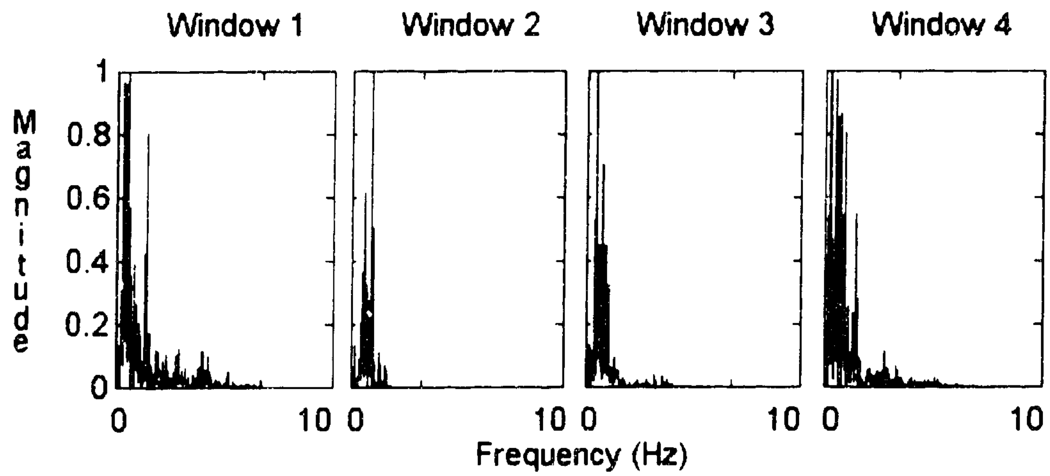

Figure 6 Windowed Frequency Response of Febme16.W

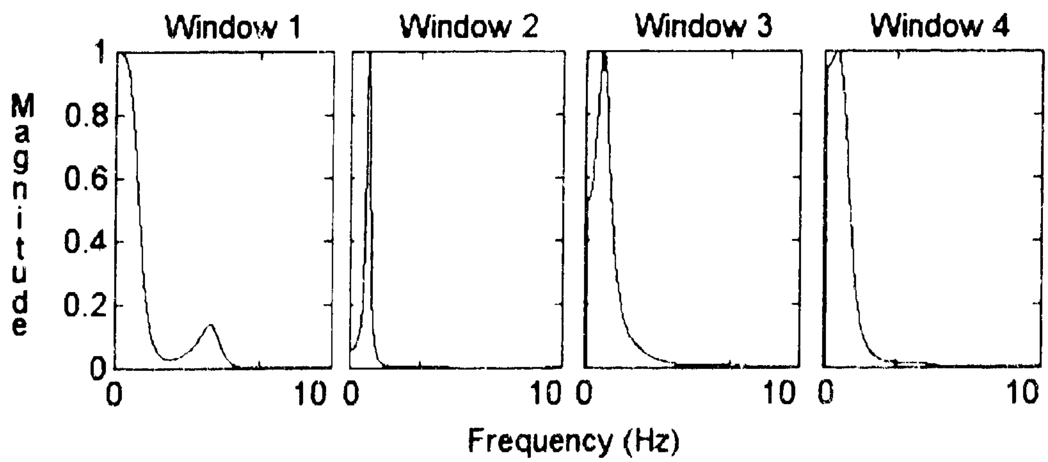

Figure 7 Frequency Response of the ARMA Model of FEBME16.W

5.0 NEURAL NETWORK IMPLEMENTATION

Currently, there are several types of neural network algorithms available for use. These networks are developed based upon various learning methods or processes including synaptic learning, linear associator, adaptive resonance, autoassociation, and feature detection. A few of the more popular neural network types are back-propagation, ART, Hopfield, neocognitron, Kohonen, and ADALINE.

For this research, two neural networks were chosen, back-propagation and supervised Kohonen. These networks were used due to their ease in implementation, learning processes, and for their differences in classification procedures.

Prior to discussing the usage and results of the networks, a description of the basic neural network model is presented.

5.1 Neural Network Model

Pattern recognition techniques have been used since the early 1950's when the field of neural networks was introduced [22]. One early type of neural network was the perceptron [37]. Simply stated, a perceptron is a node which takes a set of inputs, multiplies them by a weighted value, then sums the terms. The result is a single weighted value related to the input terms which can be expressed mathematically as

$$NET = i_1W_1 + i_2W_2 + \ldots + i_nW_n \qquad (5.1.1)$$

A diagram of a perceptron is shown in Figure 8

One problem with a perceptron is that the output is unbounded. This can cause overflow conditions in digital systems and saturation in analog systems. In creating a bounded perceptron output, the neuron was developed. A neuron provides the basic building block of a neural network [37] (see Figure 9).

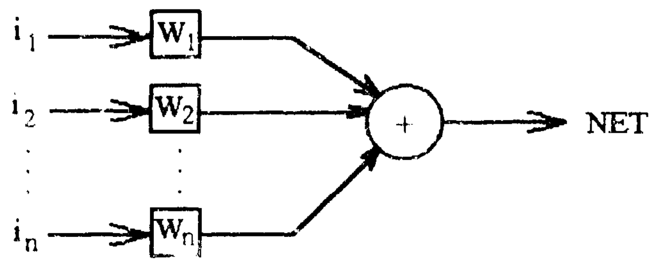

Figure 8 Perceptron Model

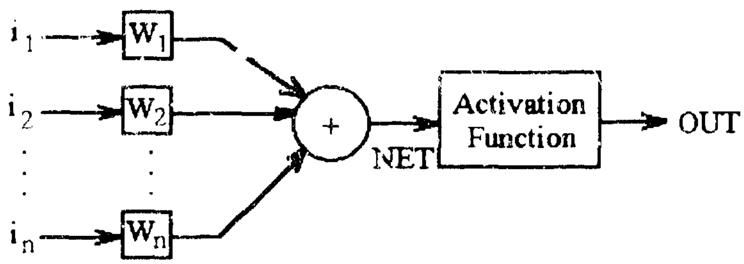

Figure 9 Neuron Model

The neuron takes the perceptron output, processes it through an activation function and produces a bounded output value as shown

$$\text{OUT} = \text{F}(\text{NET}) \qquad (5.1.2)$$

Several types of activation, or logistic, functions exist; one of the most common being the sigmoidal activation function. The sigmoid function is given by:

$$OUT = F(NET) = \frac{1}{1 + e^{-NET}} \tag{5.1.3}$$

and the first derivative becomes

$$F'(NET) = \frac{\delta OUT}{\delta NET} = OUT \cdot (1 - OUT) \tag{5.1.4}$$

A plot of the activation function output is shown in Figure 10. The sigmoid is desirable since it is continuous and has a simple derivative which is also continuous.

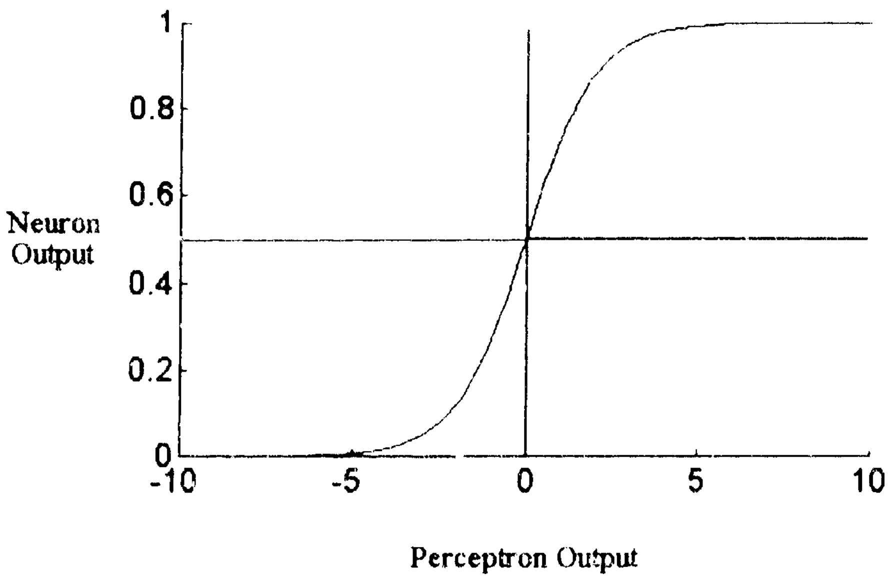

Figure 10 Sigmoidal Activation Function

The logistic function compresses the perceptron output range such that the output lies between 0 and 1. It also introduces a nonlinearity which allows for better prediction or classification in multi-layer networks [37]. The sigmoidal function provides an automatic gain control thereby eliminating network saturation. It should be noted that any non-linear function may be used providing that it is differentiable over the entire range [37].

Figure 11 illustrates a typical neural network consisting of an input layer, hidden layers, and an output layer. Each network layer may contain a different number of neurons. The input layer neurons receive data from the outside world without making any modifications. The hidden layer neurons provide intermediate calculations for internal feature maps. Hidden neurons are named as such because their inputs and outputs cannot be seen. The output layer neurons display the network results which contain the prediction or classification information. Interpretation of the output neurons depends upon the initial definition of the network.

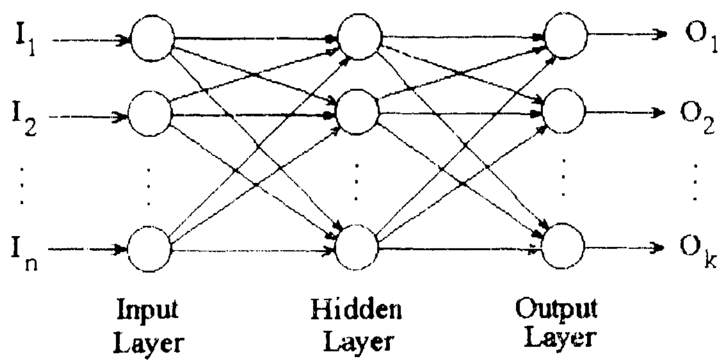

Figure 11 Basic Neural Network Model

After creating a base neural network, the next step is to decide how the network is to operate and implement a training algorithm. Network operation and training is different

for back-propagation and supervised Kohonen networks. These networks and their training is described below.

5.2 Back-Propagation Neural Networks

The back-propagation neural network gets its name from the training method. Back-propagation training is accomplished in two stages, a forward pass and a reverse pass. In the first stage, or forward pass, an input vector is applied to the network and an output vector created. The second stage, or reverse pass, calculates an error vector and propagates backwards through the network to adjust the intermediate weight vectors so as to minimize the error. Initially, the network weights are set to small random numbers to prevent the network from saturating with large numbers. The basic training steps are as follows:

Forward Pass

1. Select input information
2. Calculated output of network k

Reverse Pass

3. Calculate the error between the network and target
4. Adjust weights to minimize the error
5. Repeat steps 1-4 until error is acceptable.

Once training is complete, the network can be used for recognition or prediction, depending upon the type of training data.

In a forward pass, the output of each layer is the input to the next layer. This can be mathematically described as

$$O = F(XW) \qquad (5.2.1)$$

where X = input vector

O = output vector for given layer

W = Matrix of weights between neurons

$F()$ = activation function as described in Eq. (5.1.3).

The final output vector is calculated by stepping between the individual layers. The output from the input layer is

$$O_i = X. \qquad (5.2.2)$$

The hidden layer output vector is

$$O_h = F(O_i W_i) \qquad (5.2.3)$$

and the final output vector, Y, becomes

$$Y = F(O_h W_h) = F[\, F(O_i W_i)\, W_h] \qquad (5.2.4)$$

Now that an output vector has been calculated, the task of adjusting the weights begins. Back-propagation uses a modified version of the Delta rule to adjust the weights as follows:

$$\delta = O_j(1-O_j)(\text{TARGET}-O_j) \quad (5.2.5)$$

This δ is then multiplied by the source neuron for the weight being calculated. This product is in turn multiplied by the learning rate coefficient η (typically 0.01 to 1.0) and this result is now added to the weight. This process in mathematical matrix form is as follows:

$$\Delta W_{pq,k} = \eta * \delta_{q,k} * O_{p,j} \quad (5.2.6)$$

$$W_{pq,k}(N+1) = W_{pq,k}(N) + \Delta W_{pq,k} \quad (5.2.7)$$

where $W_{pq,k}(n)$ = value of weight from neuron p in the hidden layer to neuron q in the output layer at step N (before adjustment). k indicates that the weight is associated with its destination layer.

$W_{pq,k}(N+1)$ = value of weight @ step N+1 (after adjustment)

$\delta_{q,k}$ = the value of δ for neuron q in output layer k

$O_{p,j}$ = the value of OUT for neuron p in hidden layer j

Note: p & q refer to a specific neuron; j & k refer to a specific layer.

Back-propagation trains the hidden layers by propagating the output error back through the network layer by layer. The equations previously discussed are still valid, but they must be modified due to a lack of a TARGET vector. This modification is accomplished by first calculating the δ for the output layer, which is used to calculate δ for all the previous layers by propagating it back through all the weights. This is represented mathematically as :

$$\delta_{p,j} = O_{p,j}(1-O_{p,j})(\Sigma\, \delta_{q,k} * W_{pq,k}) \quad (5.2.8)$$

where

$$\Sigma\ \delta_{q,k} * W_{pq,k} \qquad (5.2.9)$$

is the sum of the weighted errors. Using this we can now adjust the weights using the previously discussed equations. Using vector notation:

$$D_j = D_k W_k^t \ \#\ [O_j \ \#\ (I - O_j)] \qquad (5.2.10)$$

where D_k = set of δ at output layer

W_k = set of weights for output layer

D_j = δ vector for hidden layer

= a component by component multiplication of the two vectors.

O_j = the output layer for layer j and

I = matrix where all components are 1.

5.3 Supervised Kohonen Neural Network

In the early 1970's, Tuevo Kohonen published a paper proposing a model for an associative memory, the linear associator [22]. The linear associator uses neurons with linear transfer functions rather than non-linear activation functions such as the sigmoid. The neurons respond to input changes by changing the firing rate of the outputs. This network will map similar inputs to similar outputs, leading automatically to the ability to generalize [22].

With the back-propagation neural network, the number of output layer neurons depended upon the number of classes in the data set. Each output neuron was assigned to a specific class and the interior network weights were adjusted so that for a given input vector, the output vector had a one (1) for the correct class and zero (0) for the other classes. The Kohonen neural network has a slightly different structure which is demonstrated in Figure 12.

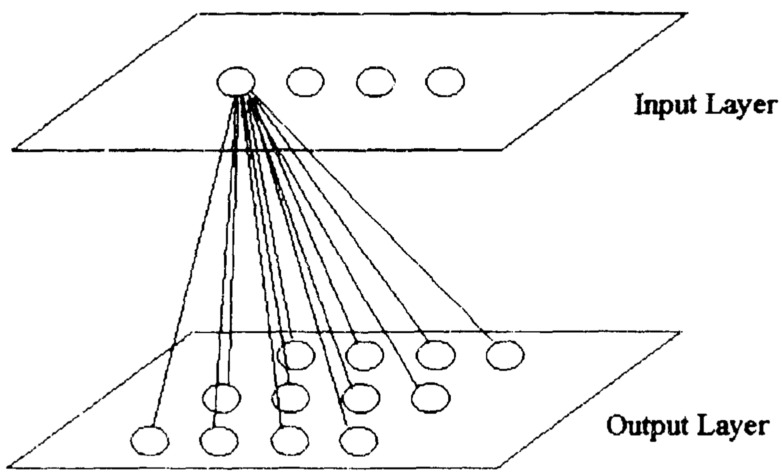

Figure 12 Kohonen Neural Network Architecture

A Kohonen network, shown in Figure 12, consists of two layers of neurons, an input layer and an output layer. This structure does not contain the hidden layer neurons of the back-propagation networks. The number of input layer neurons is determined by the input data vector length whereas the number of output layer neurons is chosen based upon the number of classes and the users intuition as to the number of neurons required to properly represent each particular class

Kohonen networks contain two types of interconnections. The first set of connections is between the input and output neurons where each input neuron is connected to each output neuron. The second set of connections allows interaction between the output neurons themselves. These output neuron interactions determine which neuron will fire and make the classification.

One advantage of Kohonen networks is the ability to self organize feature maps. During training, the output neurons are adjusted so as to cluster around groups or features of the data presented to the network. In a back-propagation network, all neuron weights are adjusted such that the neuron representing the correct class approaches a value of one (1) and the incorrect class neuron values are reduced to zero (0). In simpler terms, for each back-propagation network adjustment, every neuron is updated for error minimization. The Kohonen network is adjusted differently. For each given input only the winning neuron is adjusted. As the winning neuron is the only one adjusted, the concept of competition is introduced into the output layer. Determination of the winning neuron is accomplished through closest output neuron to the input data with respect to any given metric. One of the most common methods of choosing a winning neuron uses the Euclidean distance, whereby the winning neuron would have the smallest distance from the input vector.

At this point, it should be noted that Kohonen neurons are not handled in the same manner as back-propagation neurons. For input layer neurons, there are no differences between networks as these neurons are single valued and contain one point of the input vector. From Figure 12, it is shown that Kohonen networks do not have hidden layer neurons, however there is a significant number of output neurons as compared to the back-propagation network. The Kohonen output neurons are treated as vectors with the same number of components as the input vector. Since the lengths of the input vector and

the output neurons are equal, choosing the distance between them is a simple method of determining the winning output.

Suppose that the training data consists of n vectors with M components each. Then the Euclidean distance is calculated by

$$d[i] = \sqrt{\sum_{j=1}^{m} \left(x[i] - W[i][j] \right)^2} \qquad (5.3.1)$$

where $i = 1, 2, \ldots, n$

$x[i]$ = components of the input vector

$W[i][j]$ = elements of the weight matrix

$d[i]$ = Euclidean distance for the ith input vector

and the neuron associated with the smallest d[i] value is the winning neuron. This neuron will adjusted during training or determine the class when discriminating signals. When calculating this distance, it is not necessary to include the square root since the comparison is related to magnitude only.

The training of Kohonen networks differs from that of back-propagation nets. In a back-propagation network, an error vector is used to adjust the weight values for each neuron, whereas Kohonen networks typically adjust only the neuron that wins. Adjustment of the winning neuron uses the delta rule and a learning rate in the form

$$w\_new[i][j] = w\_old[i][j] + \lambda \left(x[j] - w[i][j] \right) \qquad (5.3.2)$$

where λ is the learning rate. The learning rate typically starts at 0.2 and decreases to 0 over the training period by

$$\lambda\_new = \lambda\_old - (\lambda\_start / N) \qquad (5.3.3)$$

where λ_start is the initial learning rate and N is the number of iterations for learning.

Kohonen learning is much simpler than back-propagation learning, but there are two possible disadvantages in its use. First, Kohonen networks are slow to learn the input data. For each input vector applied, only one output neuron has its weights adjusted. Since the weights of one neuron are affected, the other neurons are not adjusted toward or away from their respective classes. The second problem is again related to the restriction of adjusting neurons independently. If the clusters of input data are close together and the Kohonen neurons are significantly far away, most of the neurons will never be adjusted toward the data clusters. This can be easily demonstrated through a 2-space example. Figure 13 contains two data clusters represented by D_1 and D_2 and Kohonen neurons K. From this plot, it can be seen that reqardless of which input is used for training, the neuron K' will win and be adjusted toward the appropriate cluster. When the next input is applied, this same neuron will win again. As a result, the K' neuron will always win, the remaining neurons will never move toward either cluster, and the network will never distinguish between classes. This particular problem can be overcome by using supervised Kohonen learning.

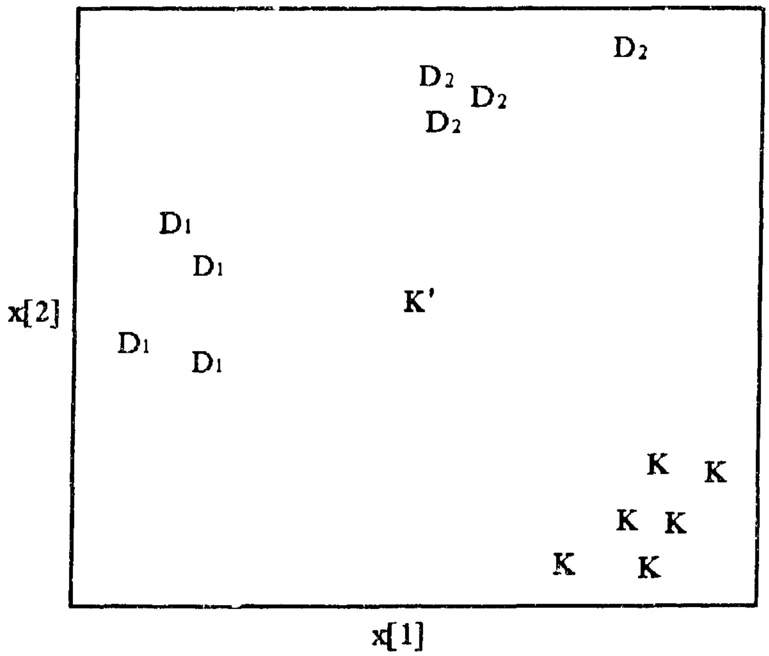

Figure 13 2-Space Vector Mapping

In supervised Kohonen networks each output neuron is assigned to a particular class. By knowing the class of the neuron and the input class, it can be determined whether the winning output neuron should be adjusted towards or away from the input vector. Using Eq. 5.3.2 will move the neuron towards the input vector while a slight modification,

$$w\_new[i][j] = w\_old[i][j] - \lambda \, (x[j] - w[i][j]), \qquad (5.3.4)$$

will increase the distance between the neuron and input. Controlling the direction of adjustment will force neurons toward their assigned class. However, this does not address the problem of adjusting all neurons toward their respective vactor spaces.

To insure that all neurons are adjusted toward their proper vector spaces, it is necessary to count the number of firings for each neuron. By monitoring neuron firings over a user defined number of training epochs, it can be determined which neurons are not being properly adjusted. After the specified number of training epochs, any neuron that has not fired, or fired few times, will be adjusted by the procedure described above.

By forcing every output neuron to be adjusted toward its assigned class, the grouping of Kohonen neurons will better represent the data clustering. As a result, the supervised Kohonen network will have good pattern recognition and noise tolerance.

5.4 Software Implementation

Currently, there are many commercial software packages that implement various types of neural networks. For this research, the neural networks implemented are included in the SeisNet neural network package which was created for use by the Applied Neural Networks Lab at West Virginia Institute of Technology [36]. This program provides a significant amout of user control over the network implementation. Several of the user determined options are as follows

total number of records

number of training records

number of testing records

number of training epochs

number of network layers

number of neurons per layer

learning rate

termination error.

Seisnet generates a report which includes the network parameters, as determined by the user, training results, and the classification results. A typical network report is included in Appendix D.

6.0 TESTING AND ANALYSIS

The detailed results of the testing for this project are included in Appendix D with a summary in Table 7. The first page of Appendix D is a typical neural network report file which contains information on network training parameters, training results, and classification results in the following order. The first section of the report gives the number of training records, testing records, network size, momentum, learning rate, and the computer on which the network was trained. Section two states the training threshold, training time per epoch, and training error values. Section three shows the training results in tabular form. Finally, section four lists the classification results in tabular form.

Since the GROUND TRUTH database at CSS was in the process of being created at the time of this testing, the number of known good signals for testing was limited to 75. Due to variations in seismic events and event types, a database of this size is limited in its ability to provide a sufficient base for proper neural network training. In order to overcome the small number of signals available, the testing was limited to five classes as follows:

class 1	quarry blast
class 2	local earthquake
class 3	teleseismic earthquake
class 4	regional earthquake
class 5	marine explosion

It was also decided to split the database such that one part of the signals were used for training and the remaining signals used for testing

The back-propagation network implemented consisted of 144 input neurons, 70 hidden neurons, and 5 output neurons where each output neuron represents one of the five event classes.

Ideally, for any given seismic event, the output vector would consist of one neuron of a value equal to 1 and four neurons with a value of zero. In reality this never happens, so a method must be implemented to chose between the five output neurons in case of contention. To be considered the winning output, the neuron must meet the following two conditions;

1. a value greater than 0.7 and
2. a value of 0.2 greater than the other four neurons.

The supervised Kohonen network consists of 144 input neurons and 360 output neurons. This configuration uses 72 neurons to represent the vector space for each class.

Signal discrimination in supervised Kohonen networks do not require the post-processing of back-propagation networks. This is due to each output neuron having a designated class. Since only one neuron may fire for any given input, signal discrimination is determined by the class designation of the winning neuron.

6.1 Test Results

A statistical average for training and testing can be obtained using the database splitting method mentioned above. Before splitting the database the signal order was randomized to prevent the network from learning the pattern in which they were presented

to the network. To build a statistical base, 20 randomized data sets were generated. These randomized sets were then divided into two groups. The first group was split into 30 signals for training and 45 for testing while the split for the second group were reversed, 45 for training and 30 for testing. The complete results from this procedure are shown in Appendix D where the tests denoted by SP1 to SP10 are the 30/45 split and SP11 to SP20 are the 45/30 split.

Back-propagation Network

Class	1	2	3	4	5
30 / 45 Split	2.11	9.33	33.01	8.18	18.10
45 / 30 Split	0.00	10.27	36.98	1.43	32.26

Supervised Kohonan Network

Class	1	2	3	4	5
30 / 45 Split	53.38	25.85	47.58	37.04	49.21
45 / 30 Split	57.58	26.94	67.83	22.40	27.50

Table 7 Network Classification Results (%)

Table 7 presents the average classification results per class. These results were obtained after 10000 training iterations for the back-propagation network and 2500 iterations for the supervised Kohonen network. The back-propagation network, based upon the information in Table 7, does not prove to be useful in discrimination of seismic signals using the ARMA coefficient model. However, the supervised Kohonen network

yields significantly higher recognition rates. This is most likely due to the noise tolerance of Kohonen networks.

6.2 Training Time

Training of the neural networks varies between different computers as would be expected. The average training times of the back-propagation and Kohonen networks for the different database splits is shown in Table 8.

Back-propagation Network

	IBM PS70 386 - DX 20 MHz	Gateway 486 - DX2 50 Mhz	Flex 486 - DX 50 Mhz
30 / 45 Split	27.45	4.80	3.39
45 / 30 Split	41.02	7.43	5.05

Supervised Kohonan Network

	IBM PS70 386 - DX 20 MHz	Gateway 486 - DX2 50 Mhz	Flex 486 - DX 50 Mhz
30 / 45 Split	23.69	3.48	2.66
45 / 30 Split	36.11	5.78	3.81

Table 8 Average Network Training Times (sec / epoch)

6.3 Summary

Overall, the results of this study demonstrate that the ARMA coefficient model is insufficient as a stand alone seismic signal discriminator. The classification results of the back-propagation network are poor at best. Back-propagation does acheive a recognition rate of 36.98% for teleseismic events but, this is not a promising number. The supervised Kohonen network, however, has recognition rates of 67.83% for teleseismic events and 57.58% for quarry blasts.

This information suggests that a supervised Kohonan network using ARMA modeling in conjunction with other preprocessing techniques could produce an acceptable seismic signal discriminator.

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APPENDIX A Data Base Wave Form Files from CSS

FNAME	STA	CHAN	JDATE
Febme1.w	ARU	bz	1991119
Febme16.w	ESLA	sz	1991114
Febme17.w	ESLA	sz	1991114
Febme18.w	ESLA	sz	1991135
Febme19.w	ESLA	sz	1991135
Febme43.w	GAR	bz	1990051
Febme45.w	GAR	bz	1991124
Febme47.w	GAR	bz	1991139
Febme48.w	GAR	bz	1991141
Febme49.w	GAR	bz	1991146
Febme55.w	KIV	bz	1991133
Febme56.w	KIV	bz	1991146
Febme65.w	OBN	bz	1991139
Febme66.w	OBN	bz	1991144
Febme67.w	OBN	bz	1991146
Febr0.w	GRA1	bz	1990331
Febr9.w	GRA1	bz	1991117
Febr15.w	GRA1	bz	1991127
Febr21.w	GRA1	bz	1991136
Febr46.w	WRA	sz	1990331
Febr52.w	WRA	cb	1991114
Febr58.w	WRA	cb	1991119
Febr66.w	WRA	cb	1991121
Febr72.w	WRA	cb	1991129
Febr86.w	WRA	cb	1991141
Febr99.w	WRA	cb	1991143
Febr103.w	WRA	cb	1991147
Febr109.w	WRA	cb	1991151
Febr112.w	WRA	cb	1991152
Febr115.w	WRA	cb	1991153

NOTE: All signals are 2400 samples at 20.00 samples per second.

APPENDIX A Data Base Wave Form Files from CSS

FNAME	STA	CHAN	JDATE
Febta25.w	GRA1	bz	1991132
Febta52.w	WRA	sz	1990123
Febta69.w	WRA	sz	1990334
Febta78.w	WRA	sz	1990335
Febta81.w	WRA	sz	1990335
Febta86.w	WRA	sz	1990051
Febta97.w	WRA	sz	1990065
Febta150.w	WRA	cb	1991114
Febta177.w	WRA	cb	1991118
Febta229.w	WRA	cb	1991121
Febta309.w	WRA	cb	1991125
Febta317.w	WRA	cb	1991125
Febta408.w	WRA	cb	1991133
Febta513.w	WRA	cb	1991137
Febta542.w	WRA	cb	1991138
Febla0.w	BJT	sz	1991147
Febla5.w	GAR	bz	1991115
Febla7.w	GAR	bz	1991117
Febla8.w	GAR	bz	1991119
Febla9.w	GAR	bz	1991145
Febla11.w	GRA1	bz	1991112
Febla13.w	GRA1	bz	1991116
Febla16.w	GRA1	bz	1991122
Febla19.w	GRA1	bz	1991149
Febla20.w	HFS	sz	1991135
Febla26.w	HFS	cb	1991135
Febla73.w	WRA	cb	1991137
Febla75.w	WRA	cb	1991143
Febla76.w	WRA	cb	1991143
Febla82.w	WRA	cb	1991146

NOTE: All signals are 2400 samples at 20.00 samples per second.

APPENDIX A Data Base Wave Form Files from CSS

FNAME	STA	CHAN	JDATE
Febqb0.w	ASAR	cb	1991123
Febqb12.w	CTA	bz	1991123
Febqb20.w	CTA	bz	1991141
Febqb33.w	KAF	sz	1990331
Febqb45.w	KAF	sz	1991114
Febqb93.w	KAF	sz	1991133
Febqb100.w	KAF	sz	1991135
Febqb114.w	KAF	sz	1991140
Febqb117.w	KAF	sz	1991140
Febqb118.w	KAF	sz	1991140
Febqb122.w	KAF	sz	1991142
Febqb147.w	KAF	sz	1991150
Febqb154.w	KAF	sz	1991154
Febqb158.w	STK	bz	1991121
Febqb180.w	WRA	cb	1991141

NOTE: All signals are 2400 samples at 20.00 samples per second.

APPENDIX B GSETT-Subset1 Station Names and Locations

STA	STATION NAME	LATITUDE	LONGITUDE
ARU	ARTI - SVERDLOVSK, OBLAST	56.4000	58.6000
ASAR	ALICE SPRINGS ARRAY - NORTH TERRITORY, AUSTRALIA	23.7040	133.9620
BJT	BAIJIATUAN - BAIJIATUAN, CHINA	40.0403	116.1750
CTA	CHARTERS TOWERS - QUEENSLAND, AUSTRALIA	20.0880	146.2540
ESLA	SONSECA ARRAY STATION - SPAIN	39.6700	-3.9600
GAR	GARM - GARM, USSR	39.0000	70.3000
GRA1	GRAFENBERG ARRAY - BOYERN, GERMANY	49.6920	11.2220
HFS	HAGFORS ARRAY - SWEDEN	60.1335	13.6836
KAF	KANGASNIEMI - FINLAND	62.1127	26.3062
KIV	KISLOVODSK - WESTERN CAUCASUS USSR	43.9500	42.6833
OBN	OBNINSK - OBNINSK, USSR	55.1167	36.5667
STK	STEPHENS CREEK - NEW SOUTH WALES, AUSTRALIA	31.8820	141.5920
WRA	WARRAMUNGA ARRAY - NORTH TERRITORY, AUSTRALIA	-19.7657	134.3891

APPENDIX C ARMA Coefficient Extraction Routine

```
%-----------------------------------------------------------------------------------
% File: ARMA.M       (Matlab Script File)
%-----------------------------------------------------------------------------------
% Author:     John R. Martin
% Date:       01-26-1993
%-----------------------------------------------------------------------------------
% Purpose:    This program calculates the auto-regressive-moving average
%             coefficients for an equivalent approximation of the time series.
%             The results are stored with the numerator coefficients then
%             denominator coefficients per window for the given number of
%             windows.
%-----------------------------------------------------------------------------------
% Changes:    08-18-93  JRM  Store data on individual basis not as full matrix.
%-----------------------------------------------------------------------------------

clear;
clc;
clf;

%-------------------------------
% Variable List
%-------------------------------
wave_dir   = 'c:\data\ss1';          % dir for *.w files
out_file   = 'c:\data\arma.dat';     % output filename
index_filename                       = 'file'; % name of index file
no_class   = 5;                      % number of classes
slice      = 16;                     % number of time slices
filt_ord   = 4;                      % order of ARMA filter
auto_len   = 1;                      % automatic samples/window
no_samp    = 0;                      % manual samples/window
                                     % Ignored if auto_len = 1
graphics   = 1;                      % 0 - no graphics
                                     % 1 - create plots
norm       = 2;                      % 0 - no Normalization
                                     % 1 - normalize input data
                                     % 2 - normalize output data
win_type   = 0;                      % 0 - Rectangular
                                     % 1 - Hamming
                                     % 2 - Hanning
```

APPENDIX C ARMA Coefficient Extraction Routine

```
%--------------------------------
% External Variables
%--------------------------------
% These Variables should be in the file pointed to by index_filename
%
% File = []           The name of the waveforms
% class = []          The class of the waveforms in the same order as
%                             the file name listing
% wave_length         Length in samples of the waveforms
%                             should be the same per waveform.
% file_number         Number of waveforms
%

%--------------------------------
% Begin Executable Code
%--------------------------------
% Get File Index
%--------------------------------
disp([' ']);
disp (['Auto-Regressive Moving Average Extraction Routine']);
disp([' ']);
disp (['Loading Waveform Index from ',wave_dir]);

eval (index_filename);          %Loads File Prefix FILE.M
clear index_filename;

%--------------------------------
% Create the Output Data File
%--------------------------------
FID = -1;                   % -1 is default for failure to open file
while FID == -1
   FID = fopen(out_file,'at','n');       % Append ASCII format to IBM
end

data_out = zeros(1,(slice/4)*(filt_ord+filt_ord+1)+no_class);

%--------------------------------
% Waveform loop
%--------------------------------
```

APPENDIX C ARMA Coefficient Extraction Routine

```
% Remove blanks from the filename
for file_no = 1:file_number
    clf;
    namesize = 0;
    for character = 1:8
        if strcmp(File(file_no,character),' ') == 0
            namesize = namesize + 1;
        end
    end

    % Get name from the filelist
    fname = File(file_no,1:namesize);

    % Diplays which file is currently be worked on
    disp(['   Evaluating:  ',fname]);

    % Retreives the datafile from the waveform_directory
    eval (['load ',wave_dir,'\',fname,'.w']);

    eval(['data=',fname,';']);          % assign to working variable
    eval(['clear ',fname]);             % free variable from memory

    if auto_len == 1
        no_samp = wave_length / slice;
    end

    % Calculate the window smoothing
    if file_no == 1
        for n = 1:no_samp
            if win_type == 0                    % Rectangular
                window(n) = 1;
            end
            if win_type == 1                    % Hamming
                window(n) = 0.54 - 0.46*cos((2*pi*n)/no_samp);
            end
            if win_type == 2                    % Hanning
                window(n) = 0.50 - 0.50*cos((2*pi*n)/no_samp);
            end
        end
    end
```

APPENDIX C ARMA Coefficient Extraction Routine

```
% Normalize the input data
if norm == 1
    data = data / max(abs(data));
end %if

%-------------------------------
% Window loop
%-------------------------------
for win = 1:slice/4
    disp(win)
    start = (win-1) * no_samp + 1;
    stop = win * no_samp;
    win_data = data(1,start:stop);
    if win_data(1) == 0
        win_data(1) = .01;
    end

    %-------------------------------
    % Get ARMA filter coefficients
    %-------------------------------
    [b,a] = prony(win_data, filt_ord, filt_ord);

    %-------------------------------
    % store data
    %-------------------------------
    start = (win-1)*(filt_ord+filt_ord+1)+1;
    stop = win*(filt_ord+filt_ord+1);
    data_out(1,start:stop) = [b a(1,2:filt_ord+1)];

    %-------------------------------
    % compare frequency response of fft and arma
    %-------------------------------
    freq = fft(win_data);
    tmp = size(freq);
    f = freq(1:tmp(2)/2)/max(abs(freq));
    [h,n] = freqz(b,a,tmp(2)/2);
    h = h/max(abs(h));
```

APPENDIX C ARMA Coefficient Extraction Routine

```
        %-------------------------------
        % Plot Graphics
        %-------------------------------
        if graphics == 1
            clf;
            plot(1:tmp(2)/2,abs(f),1:tmp(2)/2,abs(h));
            title(['FFT / ARMA Response Plot']);
            xlabel(['Frequency']);
            ylabel(['Magnitude']);
        end
    end% window loop

    %------------------------------
    % Normalize the output data
    %------------------------------
    if norm == 2
        data_out(1,:) = data_out(1,:)/max(abs(data_out(1,:)));
    end

    %------------------------------
    % Class identifier
    %------------------------------
    if class(file_no) == 1,          classifier = [1.0 0.0 0.0 0.0 0.0];
    elseif class(file_no) == 2,  classifier = [0.0 1.0 0.0 0.0 0.0];
    elseif class(file_no) == 3,  classifier = [0.0 0.0 1.0 0.0 0.0];
    elseif class(file_no) == 4,  classifier = [0.0 0.0 0.0 1.0 0.0];
    elseif class(file_no) == 5,  classifier = [0.0 0.0 0.0 0.0 1.0];
    end

    %------------------------------
    % Save data in ASCII format
    %------------------------------
    for count = 1:63,
        fprintf(FID, ' %12.8f', data_out(1,count));
    end
    fprintf(FID, ' %3.1f %3.1f %3.1f %3.1f %3.1f\n', classifier);
end% waveform loop

fclose(FID);
```

APPENDIX D Neural Network Data

Typical Neural Network Classification Report

Network: Back Propagation Run Date: 7/ 8/1993

Input Data

Waveform File Name	SP1A1.PRM
Number of Data Records	75
Number of Training Records	30
Number of Testing Records	45
Number of Training Epochs	10000
Number of Network Layers	3
Number of Neurons Per Layer	144 70 5
Learning Rate Delta	0.2000
Momentum	0.1000
Termination Error	0.000E+00
Saving Weight in	SP1A1.BWT
Computer	20 MHz IBM Model 70

Training Summary

Training Threshold	0.7000
Training Threshold Difference	0.2000
Average Time Per Epoch (sec)	28.10
Ave. Error	7.187E-05
Max. Error	1.691E-04
Min. Error	8.139E-06

		Output Class 0	1	2	3	4	5	Percent Correct
	1	0/6	6/6	0/6	0/6	0/6	0/6	100.00
Input	2	0/4	0/4	4/4	0/4	0/4	0/4	100.00
Class	3	0/5	0/5	0/5	5/5	0/5	0/5	100.00
	4	0/9	0/9	0/9	0/9	9/9	0/9	100.00
	5	0/6	0/6	0/6	0/6	0/6	6/6	100.00

Classification Summary

Classification Threshold	0.7000
Classification Threshold Difference	0.2000

		Output Class 0	1	2	3	4	5	Percent Correct
	1	5/9	1/9	2/9	0/9	1/9	0/9	11.11
Input	2	5/11	1/11	0/11	0/11	3/11	2/11	0.00
Class	3	5/10	1/10	0/10	2/10	2/10	0/10	20.00
	4	4/6	0/6	1/6	0/6	1/6	0/6	16.67
	5	3/9	1/9	3/9	0/9	1/9	0/9	0.00

APPENDIX D Neural Network Data

Back-propagation Neural Network Training Data

	Input Class	Output Class 0	1	2	3	4	5	Total	% CORR
SP1	1	0	6	0	0	0	0	6	100.00
	2	0	0	4	0	0	0	4	100.00
	3	0	0	0	5	0	0	5	100.00
	4	0	0	0	0	9	0	9	100.00
	5	0	0	0	0	0	6	6	100.00
SP2	1	0	3	0	0	0	0	3	100.00
	2	0	0	6	0	0	0	6	100.00
	3	0	0	0	6	0	0	6	100.00
	4	0	0	0	0	7	0	7	100.00
	5	0	0	0	0	0	8	8	100.00
SP3	1	0	6	0	0	0	0	6	100.00
	2	1	0	5	0	0	0	6	83.33
	3	0	0	0	5	0	0	5	100.00
	4	0	0	0	0	4	0	4	100.00
	5	0	0	0	0	0	9	9	100.00
SP4	1	0	5	0	0	0	0	5	100.00
	2	0	0	7	0	0	0	7	100.00
	3	2	0	0	2	0	0	4	50.00
	4	0	0	0	0	7	0	7	100.00
	5	0	0	0	0	0	7	7	100.00
SP5	1	0	4	0	0	0	0	4	100.00
	2	0	0	8	0	0	0	8	100.00
	3	1	0	0	6	0	0	7	85.71
	4	0	0	0	0	4	0	4	100.00
	5	0	0	0	0	0	7	7	100.00
SP6	1	0	5	0	0	0	0	5	100.00
	2	0	0	6	0	0	0	6	100.00
	3	0	0	0	6	0	0	6	100.00
	4	0	0	0	0	6	0	6	100.00
	5	0	0	0	0	0	7	7	100.00
SP7	1	0	4	0	0	0	0	4	100.00
	2	0	0	8	0	0	0	8	100.00
	3	1	0	0	2	0	0	3	66.67
	4	0	0	0	0	8	0	8	100.00
	5	0	0	0	0	0	7	7	100.00

APPENDIX D Neural Network Data

Back-propagation Neural Network Training Data

	Input Class	Output Class 0	1	2	3	4	5	Total	% CORR
SP8	1	0	3	0	0	0	0	3	100.00
	2	0	0	7	0	0	0	7	100.00
	3	1	0	0	5	0	0	6	83.33
	4	0	0	0	0	6	0	6	100.00
	5	0	0	0	0	0	8	8	100.00
SP9	1	0	5	0	0	0	0	5	100.00
	2	0	0	7	0	0	0	7	100.00
	3	2	0	0	3	0	0	5	60.00
	4	1	0	0	0	4	0	5	80.00
	5	0	0	0	0	0	8	8	100.00
SP10	1	0	8	0	0	0	0	8	100.00
	2	0	0	5	0	0	0	5	100.00
	3	0	0	0	7	0	0	7	100.00
	4	0	0	0	0	7	0	7	100.00
	5	0	0	0	0	0	3	3	100.00
SP11	1	0	9	0	0	0	0	9	100.00
	2	0	0	11	0	0	0	11	100.00
	3	2	0	0	8	0	0	10	80.00
	4	0	0	0	0	6	0	6	100.00
	5	0	0	0	0	0	9	9	100.00
SP12	1	0	12	0	0	0	0	12	100.00
	2	0	0	9	0	0	0	9	100.00
	3	3	0	0	6	0	0	9	66.67
	4	1	0	0	0	7	0	8	87.50
	5	0	0	0	0	0	7	7	100.00
SP13	1	1	8	0	0	0	0	9	88.89
	2	0	0	9	0	0	0	9	100.00
	3	0	0	0	10	0	0	10	100.00
	4	0	0	0	0	11	0	11	100.00
	5	0	0	0	0	0	6	6	100.00
SP14	1	0	10	0	0	0	0	10	100.00
	2	0	0	8	0	0	0	8	100.00
	3	0	0	0	11	0	0	11	100.00
	4	0	0	0	0	8	0	8	100.00
	5	0	0	0	0	0	8	8	100.00

APPENDIX D Neural Network Data

Back-propagation Neural Network Training Data

	Input Class	Output Class 0	1	2	3	4	5	Total	% CORR
SP15	1	0	11	0	0	0	0	11	100.00
	2	1	0	6	0	0	0	7	85.71
	3	1	0	0	8	0	0	8	100.00
	4	2	0	0	0	9	0	11	81.82
	5	0	0	0	0	0	8	8	100.00
SP16	1	1	9	0	0	0	0	10	90.00
	2	0	0	9	0	0	0	9	100.00
	3	2	0	0	7	0	0	9	77.78
	4	0	0	0	0	9	0	9	100.00
	5	0	0	0	0	0	8	8	100.00
SP17	1	0	11	0	0	0	0	11	100.00
	2	1	0	6	0	0	0	7	85.71
	3	2	0	0	10	0	0	12	83.33
	4	0	0	0	0	7	0	7	100.00
	5	0	0	0	0	0	8	8	100.00
SP18	1	1	11	0	0	0	0	12	91.67
	2	0	0	8	0	0	0	8	100.00
	3	0	0	0	9	0	0	9	100.00
	4	0	0	0	0	9	0	9	100.00
	5	0	0	0	0	0	7	7	100.00
SP19	1	0	10	0	0	0	0	10	100.00
	2	0	0	8	0	0	0	8	100.00
	3	1	0	0	9	0	0	10	90.00
	4	0	0	0	0	10	0	10	100.00
	5	0	0	0	0	0	7	7	100.00
SP20	1	0	7	0	0	0	0	7	100.00
	2	0	0	10	0	0	0	10	100.00
	3	3	0	0	5	0	0	8	62.50
	4	0	0	0	0	8	0	8	100.00
	5	0	0	0	0	0	12	12	100.00

APPENDIX D Neural Network Data

Back-propagation Neural Network Classification Data

	Input Class	Output Class 0	1	2	3	4	5	Total	% CORR
SP1	1	5	1	2	0	1	0	9	11.11
	2	5	1	0	0	3	2	11	0.00
	3	5	1	0	2	2	0	10	20.00
	4	4	0	1	0	1	0	6	16.67
	5	3	1	3	0	2	0	9	0.00
SP2	1	4	0	1	2	5	0	12	0.00
	2	5	0	0	3	1	0	9	0.00
	3	4	0	0	5	0	0	9	55.56
	4	4	1	2	1	0	0	8	0.00
	5	0	0	1	0	0	0	7	0.00
SP3	1	7	0	1	0	1	0	9	0.00
	2	6	0	0	0	2	1	9	0.00
	3	6	0	0	2	2	0	10	20.00
	4	7	0	0	0	2	2	11	18.18
	5	4	0	0	0	0	2	6	33.33
SP4	1	5	1	0	1	2	1	10	10.00
	2	4	0	0	0	0	4	8	0.00
	3	5	0	2	3	1	0	11	27.27
	4	5	1	2	0	0	0	8	0.00
	5	3	1	0	0	0	4	8	50.00
SP5	1	6	0	0	1	3	1	11	0.00
	2	6	0	0	0	0	1	7	0.00
	3	5	0	0	3	0	0	8	37.50
	4	6	0	2	2	1	0	11	9.09
	5	3	0	2	0	1	2	8	25.00
SP6	1	4	0	0	1	4	1	10	0.00
	2	5	1	1	1	0	1	9	11.11
	3	4	0	2	3	0	0	9	33.33
	4	3	0	2	2	0	2	9	0.00
	5	2	0	2	0	1	3	8	37.50
SP7	1	4	0	4	0	0	3	11	0.00
	2	1	0	4	0	1	1	7	57.14
	3	8	0	2	1	0	1	12	8.33
	4	2	0	3	0	1	1	7	14.29
	5	4	0	3	0	0	1	8	12.50

APPENDIX D Neural Network Data

Back-propagation Neural Network Classification Data

	Input Class	Output Class 0	1	2	3	4	5	Total	% CORR
SP8	1	5	0	3	1	2	1	12	0.00
	2	3	0	1	3	1	0	8	12.50
	3	3	0	1	5	0	0	9	55.56
	4	7	0	1	0	1	0	9	11.11
	5	3	0	4	0	0	0	7	0.00
SP9	1	6	0	2	0	1	1	10	0.00
	2	6	0	1	0	0	1	8	12.50
	3	6	0	3	1	0	0	10	10.00
	4	6	0	4	0	0	0	10	0.00
	5	5	0	1	0	0	1	7	14.29
SP10	1	4	0	0	0	3	0	7	0.00
	2	6	2	0	1	1	0	10	0.00
	3	1	1	0	5	1	0	8	62.50
	4	4	2	0	1	1	0	8	12.50
	5	6	1	1	1	2	1	12	8.33
SP11	1	4	0	1	0	1	0	6	0.00
	2	1	0	1	0	0	2	4	25.00
	3	4	0	0	1	0	0	5	20.00
	4	5	0	4	0	0	0	9	0.00
	5	2	0	4	0	0	0	6	0.00
SP12	1	1	0	1	0	1	0	3	0.00
	2	3	0	0	1	0	2	6	0.00
	3	1	0	2	3	0	0	6	50.00
	4	3	1	2	0	1	0	7	14.29
	5	1	0	1	0	1	5	8	62.50
SP13	1	3	0	1	0	2	0	6	0.00
	2	1	1	1	2	0	1	6	16.67
	3	5	0	0	0	0	0	5	0.00
	4	3	0	0	1	0	0	4	0.00
	5	3	0	1	1	1	3	9	33.33
SP14	1	1	0	0	2	1	1	5	0.00
	2	2	3	0	2	0	0	7	0.00
	3	0	0	0	3	1	0	4	75.00
	4	6	0	1	0	0	0	7	0.00
	5	3	0	2	0	0	2	7	28.57

APPENDIX D Neural Network Data

Back-propagation Neural Network Classification Data

	Input Class	Output Class 0	1	2	3	4	5	Total	% CORR
SP15	1	2	0	0	2	0	0	4	0.00
	2	4	0	1	2	0	1	8	12.50
	3	4	0	0	3	0	0	7	42.86
	4	4	0	0	0	0	0	4	0.00
	5	5	0	0	0	0	2	7	28.57
SP16	1	3	0	0	1	1	0	5	0.00
	2	3	0	0	2	0	1	6	0.00
	3	2	0	1	3	0	0	6	50.00
	4	3	1	1	1	0	0	6	0.00
	5	4	0	0	0	0	3	7	42.86
SP17	1	3	0	0	0	1	0	4	0.00
	2	6	0	0	2	0	0	8	0.00
	3	2	0	0	1	0	0	3	33.33
	4	6	0	1	1	0	0	8	0.00
	5	0	2	2	0	2	1	7	14.29
SP18	1	0	0	0	1	2	0	3	0.00
	2	4	0	0	0	1	2	7	0.00
	3	2	0	0	3	1	0	6	50.00
	4	1	3	1	1	0	0	6	0.00
	5	1	1	2	0	4	0	8	0.00
SP19	1	1	0	2	0	2	0	5	0.00
	2	3	0	2	1	0	1	7	28.57
	3	4	0	0	1	0	0	5	20.00
	4	5	0	0	0	0	0	5	0.00
	5	3	0	2	1	1	1	8	12.50
SP20	1	5	0	1	0	0	2	8	0.00
	2	0	0	1	2	0	2	5	20.00
	3	3	0	2	2	0	0	7	28.57
	4	3	1	3	0	0	0	7	0.00
	5	0	0	0	0	0	3	3	100.00

APPENDIX D Neural Network Data

Supervised Kohonan Neural Network Training Data

Input Class		Output Class 0	1	2	3	4	5	Total	% CORR
SP1	1	0	6	0	0	0	0	6	100.00
	2	0	0	4	0	0	0	4	100.00
	3	0	0	0	5	0	0	5	100.00
	4	0	0	0	0	9	0	9	100.00
	5	0	0	0	0	0	6	6	100.00
SP2	1	0	3	0	0	0	0	3	100.00
	2	0	0	6	0	0	0	6	100.00
	3	0	0	0	6	0	0	6	100.00
	4	0	0	0	0	7	0	7	100.00
	5	0	0	0	0	0	8	8	100.00
SP3	1	0	6	0	0	0	0	6	100.00
	2	0	0	6	0	0	0	6	100.00
	3	0	0	0	5	0	0	5	100.00
	4	0	0	0	0	4	0	4	100.00
	5	0	0	0	0	0	9	9	100.00
SP4	1	0	5	0	0	0	0	5	100.00
	2	0	0	7	0	0	0	7	100.00
	3	0	0	0	4	0	0	4	100.00
	4	0	0	0	0	7	0	7	100.00
	5	0	0	0	0	0	7	7	100.00
SP5	1	0	4	0	0	0	0	4	100.00
	2	0	0	8	0	0	0	8	100.00
	3	0	0	0	7	0	0	7	100.00
	4	0	0	0	0	4	0	4	100.00
	5	0	0	0	0	0	7	7	100.00
SP6	1	0	5	0	0	0	0	5	100.00
	2	0	0	6	0	0	0	6	100.00
	3	0	0	0	6	0	0	6	100.00
	4	0	0	0	0	6	0	6	100.00
	5	0	0	0	0	0	7	7	100.00
SP7	1	0	4	0	0	0	0	4	100.00
	2	0	0	8	0	0	0	8	100.00
	3	0	0	0	3	0	0	3	100.00
	4	0	0	0	0	8	0	8	100.00
	5	0	0	0	0	0	7	7	100.00

APPENDIX D Neural Network Data

Supervised Kohonan Neural Network Training Data

	Input Class	Output Class 0	1	2	3	4	5	Total	% CORR
SP8	1	0	3	0	0	0	0	3	100.00
	2	0	0	7	0	0	0	7	100.00
	3	0	0	0	6	0	0	6	100.00
	4	0	0	0	0	6	0	6	100.00
	5	0	0	0	0	0	8	8	100.00
SP9	1	0	5	0	0	0	0	5	100.00
	2	0	0	7	0	0	0	7	100.00
	3	0	0	0	5	0	0	5	100.00
	4	0	0	0	0	5	0	5	100.00
	5	0	0	0	0	0	8	8	100.00
SP10	1	0	8	0	0	0	0	8	100.00
	2	0	0	5	0	0	0	5	100.00
	3	0	0	0	7	0	0	7	100.00
	4	0	0	0	0	7	0	7	100.00
	5	0	0	0	0	0	3	3	100.00
SP11	1	0	9	0	0	0	0	9	100.00
	2	0	0	11	0	0	0	11	100.00
	3	0	0	0	10	0	0	10	100.00
	4	0	0	0	0	6	0	6	100.00
	5	0	0	0	0	0	9	9	100.00
SP12	1	0	12	0	0	0	0	12	100.00
	2	0	0	9	0	0	0	9	100.00
	3	0	0	0	9	0	0	9	100.00
	4	0	0	0	0	8	0	8	100.00
	5	0	0	0	0	0	7	7	100.00
SP13	1	0	9	0	0	0	0	9	100.00
	2	0	0	9	0	0	0	9	100.00
	3	0	0	0	10	0	0	10	100.00
	4	0	0	0	0	11	0	11	100.00
	5	0	0	0	0	0	6	6	100.00
SP14	1	0	10	0	0	0	0	10	100.00
	2	0	0	8	0	0	0	8	100.00
	3	0	0	0	11	0	0	11	100.00
	4	0	0	0	0	8	0	8	100.00
	5	0	0	0	0	0	8	8	100.00

APPENDIX D Neural Network Data

Supervised Kohonan Neural Network Training Data

	Input Class	Output Class 0	1	2	3	4	5	Total	% CORR
SP15	1	0	10	0	0	1	0	11	90.91
	2	0	0	7	0	0	0	7	100.00
	3	0	0	0	8	0	0	8	100.00
	4	0	0	0	0	11	0	11	100.00
	5	0	0	0	0	0	8	8	100.00
SP16	1	0	10	0	0	0	0	10	100.00
	2	0	0	9	0	0	0	9	100.00
	3	0	0	0	9	0	0	9	100.00
	4	0	0	0	0	9	0	9	100.00
	5	0	0	0	0	0	8	8	100.00
SP17	1	0	10	0	0	1	0	11	90.91
	2	0	0	7	0	0	0	7	100.00
	3	0	0	0	12	0	0	12	100.00
	4	0	0	1	0	7	0	7	100.00
	5	0	0	0	0	0	8	8	100.00
SP18	1	0	12	0	0	0	0	12	100.00
	2	0	0	8	0	0	0	8	100.00
	3	0	0	0	9	0	0	9	100.00
	4	0	0	0	0	9	0	9	100.00
	5	0	0	0	0	0	7	7	100.00
SP19	1	0	10	0	0	0	0	10	100.00
	2	0	0	8	0	0	0	8	100.00
	3	0	0	0	9	1	0	10	90.00
	4	0	0	0	0	10	0	10	100.00
	5	0	0	0	0	0	7	7	100.00
SP20	1	0	7	0	0	0	0	7	100.00
	2	0	0	10	0	0	0	10	100.00
	3	0	0	0	8	0	0	8	100.00
	4	0	0	0	0	8	0	8	100.00
	5	0	0	0	0	0	12	12	100.00

APPENDIX D Neural Network Data

Supervised Kohonan Neural Network Classification Data

	Input Class	Output Class 0	1	2	3	4	5	Total	% CORR
SP1	1	0	8	0	0	1	0	9	88.89
	2	0	7	1	0	1	2	11	9.09
	3	0	7	0	1	2	0	10	10.00
	4	0	4	1	0	0	1	6	0.00
	5	0	2	4	0	2	1	9	11.11
SP2	1	0	7	0	1	3	1	12	58.33
	2	0	0	0	1	4	4	9	0.00
	3	0	0	0	6	3	0	9	66.67
	4	0	0	1	0	6	1	8	75.00
	5	0	1	0	0	2	4	7	57.14
SP3	1	0	5	3	0	0	1	9	55.56
	2	0	4	3	2	0	0	9	33.33
	3	0	1	2	3	4	0	10	30.00
	4	0	0	4	1	1	5	11	9.09
	5	0	2	3	0	0	1	6	16.67
SP4	1	0	7	0	1	2	0	10	70.00
	2	0	0	2	1	0	5	8	25.00
	3	0	0	3	8	0	0	11	72.73
	4	0	0	2	1	5	0	8	62.50
	5	0	1	0	0	3	4	8	50.00
SP5	1	0	2	3	1	1	4	11	18.18
	2	0	0	3	2	1	1	7	42.86
	3	0	0	3	5	0	0	8	62.50
	4	0	0	6	0	0	5	11	0.00
	5	0	0	3	0	0	5	8	62.50
SP6	1	0	6	0	0	2	2		60.00
	2	0	2	1	1	2	3	9	11.11
	3	0	2	0	5	1	1	9	55.56
	4	0	0	1	0	2	6	9	22.22
	5	0	1	1	0	1	5	8	62.50
SP7	1	0	4	4	0	2	1	11	36.36
	2	0	0	4	0	1	2	7	57.14
	3	0	0	9	1	2	0	12	8.33
	4	0	0	2	0	4	1	7	57.14
	5	0	1	2	0	1	4	8	50.00

APPENDIX D Neural Network Data

Supervised Kohonan Neural Network Classification Data

	Input Class	Output Class 0	1	2	3	4	5	Total	% CORR
SP8	1	0	3	2	1	3	3	12	25.00
	2	0	0	0	4	2	2	8	0.00
	3	0	0	0	9	0	0	9	100.00
	4	0	0	0	1	4	4	9	44.44
	5	0	0	1	0	1	5	7	71.43
SP9	1	0	5	1	0	0	4	10	50.00
	2	0	0	4	0	0	4	8	50.00
	3	0	0	8	2	0	0	10	20.00
	4	0	0	1	1	0	8	10	0.00
	5	0	1	0	0	0	6	7	85.71
SP10	1	0	5	0	0	2	0	7	71.43
	2	0	1	3	1	5	0	10	30.00
	3	0	0	2	4	2	0	8	50.00
	4	0	0	0	0	8	0	8	100.00
	5	0	2	3	0	4	3	12	25.00
SP11	1	0	3	0	1	1	1	6	50.00
	2	0	0	0	1	1	2	4	0.00
	3	0	0	0	5	0	0	5	100.00
	4	0	0	5	0	4	0	9	44.44
	5	0	0	4	0	0	2	6	33.33
SP12	1	0	1	0	0	1	1	3	33.33
	2	0	1	1	3	0	1	6	16.67
	3	0	0	2	4	0	0	6	66.67
	4	0	2	4	1	0	0	7	0.00
	5	0	1	3	0	1	3	8	37.50
SP13	1	0	5	0	0	1	0	6	83.33
	2	0	0	1	1	3	1	6	16.67
	3	0	0	0	5	0	0	5	100.00
	4	0	0	0	2	2	0	4	50.00
	5	0	1	1	0	7	0	9	0.00
SP14	1	0	3	1	0	1	0	5	60.00
	2	0	0	3	[illegible]	1	0	7	42.86
	3	0	0	1	3	0	0	4	75.00
	4	0	1	4	0	2	0	7	28.57
	5	0	0	7	0	0	0	7	0.00

APPENDIX D Neural Network Data

Supervised Kohonan Neural Network Classification Data

	Input Class	Output Class 0	1	2	3	4	5	Total	% CORR
SP15	1	0	2	0	1	1	0	4	50.00
	2	0	3	5	0	0	0	8	62.50
	3	0	2	3	2	0	0	7	28.57
	4	0	2	2	0	0	0	4	0.00
	5	0	3	1	0	0	3	7	42.86
SP16	1	0	4	0	1	0	0	5	80.00
	2	0	0	0	4	0	2	6	0.00
	3	0	0	0	6	0	0	6	100.00
	4	0	0	0	2	4	0	6	66.67
	5	0	0	0	1	4	2	7	28.57
SP17	1	0	2	1	0	1	0	4	50.00
	2	0	2	2	2	0	2	8	25.00
	3	0	0	0	3	0	0	3	100.00
	4	0	1	5	1	0	1	8	0.00
	5	0	3	1	0	1	2	7	28.57
SP18	1	0	2	1	0	0	0	3	66.67
	2	0	3	1	0	0	3	7	14.29
	3	0	1	4	1	0	0	6	16.67
	4	0	2	4	0	0	0	6	0.00
	5	0	5	1	0	0	2	8	25.00
SP19	1	0	2	1	0	0	1	5	40.00
	2	0	1	5	1	0	0	7	71.43
	3	0	0	3	1	1	0	5	20.00
	4	0	1	3	0	1	0	5	20.00
	5	0	2	3	0	2	1	8	12.50
SP20	1	0	5	0	1	1	1	8	62.50
	2	0	0	1	2	0	2	5	20.00
	3	0	0	2	5	0	0	7	71.43
	4	0	1	2	2	1	1	7	14.29
	5	0	0	1	0	0	2	3	66.67

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